Searching for Interaction Functions in Collaborative Filtering

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Abstract

Interaction function (IFC), which captures interactions among items and users, is of great importance in collaborative filtering (CF). The inner product is the most popular IFC due to its success in low-rank matrix factorization. However, interactions in real-world applications can be highly complex. Many other operations (such as plus and concatenation) have also been proposed, and can possibly offer better performance than the inner product. In this paper, motivated by the success of automated machine learning, we propose to search for proper interaction functions (SIF) for CF tasks. We first design an expressive search space for SIF by reviewing and generalizing existing CF approaches. We then propose to represent the search space as a structured multi-layer perceptron, and design a stochastic gradient descent algorithm which can simultaneously update both architectures and learning parameters. Experimental results demonstrate that the proposed method can be much more efficient than popular AutoML approaches, and also obtain much better prediction performance than state-of-the-art CF approaches.

1 Introduction

Collaborative filtering (CF) \([16, 34]\) is an important topic in both machine learning and data mining. By capturing interactions among rows and columns in a data matrix, CF predicts the missing entries based on the observed elements. The most famous CF application is the recommender system \([24]\). The task is to estimate users' preference on items they have not yet explored. For this data matrix, rows correspond to users, columns are the items, and the entries are ratings collected. Since users usually only interact with a few items, there will be lots of missing entries in the rating matrix. Besides, CF also has been used in applications such as image inpainting in computer vision \([19]\) and link prediction in social networks analysis \([22]\). More recently, it is extended to handle tensor data (i.e., higher-order matrices) \([20, 25]\).

In the last decade, low-rank matrix factorization \([24, 29]\) has been the most popular approach to CF. It can be formulated as the following optimization problem:

\[
\min_{U,V} \sum_{(i,j) \in \Omega} \ell \left( u_i^T v_j, O_{ij} \right)^2 + \frac{\lambda}{2} \|U\|_F^2 + \frac{\lambda}{2} \|V\|_F^2,
\]

where \(\ell\) is a loss function, the observed elements are indicated by \(\Omega\) with values given by the corresponding positions in matrix \(O \in \mathbb{R}^{m \times n}\), \(\lambda \geq 0\) is a hyper-parameter, and \(u_i \in \mathbb{R}^k\) and \(v_j \in \mathbb{R}^k\) are embedded vectors for user \(i\) and item \(j\), respectively. Note that \((1)\) captures interactions between user \(u_i\) and item \(v_j\) by the inner product. This achieves good empirical performance, enjoys
Table 1: Popular human-designed interaction functions (IFCs) for CF, where $H$ is a parameter to be trained. SIF searches a proper IFC from the validation set, while others are all designed by experts.

| IFC | operation | space | predict time | recent examples |
|-----|-----------|-------|--------------|----------------|
| human-designed | $\langle u_i, v_j \rangle$ | inner product | $O((m + n)k)$ | $O(k)$ | MF [24], FM [33] |
| | $u_i - v_j$ | plus (minus) | $O((m + n)k)$ | $O(k)$ | CML [17, 40] |
| | $\max(u_i, v_j)$ | max, min | $O((m + n)k)$ | $O(k)$ | ConvMF [21] |
| | $\sigma([u_i; v_j])$ | concat | $O((m + n)k)$ | $O(k)$ | Deep&Wide [8] |
| | $\sigma([u_i \odot v_j + H[u_i; v_j]])$ | multi, concat | $O((m + n)k)$ | $O(k^2)$ | NCF [15] |
| | $u_i \ast v_j$ | conv | $O((m + n)k)$ | $O(k \log(k))$ | ConvMF [21] |
| | $u_i \otimes v_j$ | outer product | $O((m + n)k)$ | $O(k^2)$ | ConvNCF [14] |
| AutoML | SIF (proposed) | searched | $O((m + n)k)$ | $O(k)$ | —— |

sound statistical guarantees [7, 32] (e.g., the data matrix can be exactly recovered when $O$ satisfies certain incoherent conditions and the missing entries follow some distributions), and fast training [29, 12] (e.g., can be trained end-to-end by stochastic optimization).

While the inner product has many benefits, it may not yield the best performance for various CF tasks due to the complex nature of user-item interactions. For example, the plus operation, which quantizes the users’ preference based on $u_i - v_j$, has been explored in [15, 17]. The motivation is that the embedded vectors obtained from inner product do not satisfy the triangle inequality, while those from the plus operation can. Other operations (such as concatenation and convolution) have also outperformed the inner product on many CF tasks [33, 21, 14]. Due to the success of deep networks [13], the multi-layer perceptron (MLP) is also recently used as the interaction function (IFC) in CF [8, 15, 38], and achieves good performance. However, choosing and designing an IFC is not easy. Using one simple operation, such as the inner product or plus, may not be expressive enough to ensure good performance. On the other hand, directly using a MLP leads to the difficult and time-consuming task of architecture selection [41, 2].

Recently, there have been a lot of interests in automated machine learning (AutoML) [39, 18], which involves searching for an appropriate network architecture by reinforcement learning [2, 41, 42], and the fine-tuning of a classifier ensemble by Bayes optimization [11]. In this paper, motivated by the success of AutoML, we consider formulating the search for interaction functions (SIF) as an AutoML problem. Inspired by observations on existing IFCs, we first generalize the CF objective and define the SIF problem. These observations also help to identify a domain-specific and expressive search space, which not only includes many human-designed IFCs, but also covers new ones not yet explored in the literature. We further represent the SIF problem, armed with the designed search space, as a structured MLP. This enables us to derive an efficient search algorithm based on differentiable architecture search [26, 37] and proximal algorithm [40]. The algorithm can jointly train the embedding vectors and search IFCs in a stochastic end-to-end manner. It can be extended to handle tensor data. Finally, we perform experiments on CF tasks with both matrix and tensor data. Compared with the existing AutoML approaches, we show that the proposed algorithm can find better IFCs and is much more efficient. Compared with the human-designed CF methods, the proposed algorithm can achieve much better performance, while the search cost is within 5 times of human effort.

Notations. Vectors are denoted by lowercase boldface, and matrices by uppercase boldface. For two vectors $x$ and $y$, $\langle x, y \rangle$ is the inner product, $x \odot y$ is the element-wise product, $x \otimes y$ is the outer product, $|x; y|$ concatenates (denoted “concat”) two vectors to a longer one, and $x \ast y$ is the convolution (denoted “conv”). $\Tr(X)$ is the trace of a square matrix $X$, and $\|X\|_F$ is the Frobenius norm. $\|x\|_2$ is the $\ell_2$-norm of a vector $x$, and $\|x\|_0$ counts its number of nonzero elements.

2 Related Works

2.1 Interaction Functions (IFCs) for Collaborative Filtering

As mentioned in Section 1 the IFC is key to CF, with the inner product being the most popular operation [24, 7, 29]. However, due to the complex interactions among users and items, many CF models other than low-rank matrix factorization have been proposed. Examples include the
factorization machine (FM) [33], collaborative metric learning (CML) [17], convolutional matrix factorization (ConvMF) [21], Deep & Wide [8], neural collaborative filtering (NCF) [15], and convolutional neural collaborative filtering (ConvNCF) [14]. These models are summarized in Table 1. As can be seen, many operations other than the simple inner product have been used, and have achieved better performance than matrix factorization on many CF tasks. Moreover, they all have the same space complexity, which grows linearly w.r.t. \( m \), \( n \), and \( k \), but with different computation complexities. While the design of IFCs is very important, this depends highly on the given data and task, and there is no single model in Table 1 that consistently outperforms the rest across all CF tasks [34, 1]. Thus, it is of great importance to select a proper IFC from a set of customized IFC’s designed by humans, or to design a new IFC which has not been visited in the literature.

2.2 Automated Machine Learning (AutoML)

To ease the usage and design of better machine learning models, automated machine learning (AutoML) [18, 39] has become a recent hot topic. AutoML can be seen as a black-box optimization problem, as we need to search for hyper-parameters or design issues for the underneath learning model. The success of AutoML hinges on two important questions: (i) what to search, and (iii) how to search efficiently?

In AutoML, the choice of the search space is extremely important. On the one hand, the space needs to be general enough, meaning that it should include human wisdom as special cases. On the other hand, the space cannot be too general, otherwise the cost of searching in such a space can be too expensive [42, 26]. For example, early works in neural architecture search (NAS) use reinforcement learning (RL) to search among all possible designs of a convolution neural network (CNN) [2, 41]. This takes more than one thousand GPU days to obtain an architecture with comparable performance to human-designed ones. Later, the search space is cut into blocks [42], which helps reduce the cost of RL to several weeks. Once the search space is determined, the search algorithm then matters. Unlike convex optimization, there is no universal and efficient optimization for AutoML [39, 18]. We need to invent efficient algorithms to find good designs in the space. Recently, gradient descent is adapted for NAS, and DARTS [26] allows joint update of the architecture weights and learning parameters. This further cuts down the search cost to one GPU day.

3 Proposed Method

In Section 2, we have witnessed the importance of IFCs, and the difficulty of choosing or designing one for the given task and data. Similar observations have also been made in designing neural networks, which motivates NAS methods for deep networks [2, 41]. Moreover, NAS has been developed as a replacement of humans, which can discover data- and task-dependent architectures with better performance. These inspire us to search for proper IFCs in CF by AutoML approaches.

3.1 Problem Definition

First, we define the AutoML problem here and identify an expressive search space for IFCs, which includes the various operations in Table 1. Inspired by generalized matrix factorization [15, 38] and objective (1), we propose the following generalized CF objective:

\[
\min \ F(U, V, w) = \sum_{(i,j) \in \Omega} \ell \left( w^\top f(u_i, v_j), O_{ij} \right)^2 + \frac{\lambda}{2} \|U\|^2_F + \frac{\lambda}{2} \|V\|^2_F : \|w\|_2 \leq 1, \tag{2}
\]

where \( f \) is the IFC (which takes the user embedding vector \( u_i \) and item embedding vector \( v_j \) as input, and outputs a vector), and \( w \) is a learning parameter. Obviously, all the IFCs in Table 1 can be represented by using different \( f \)’s. The following Proposition shows that the constraint \( \|w\|_2 \leq 1 \) is necessary to ensure existence of a solution.

**Proposition 3.1.** If \( f \) is an operation shown in Table 1 and the \( \ell_2 \) constraint on \( w \) is removed, then \( F \) in (2) has no nonzero optimal solution when \( \lambda > 0 \).

Next, we introduce the definition of searching interaction functions (SIF) for CF.

**Definition 3.1 (SIF).** Let \( M \) be a performance measure (the lower the better) defined on the validation set \( \bar{\Omega} \), and \( \mathcal{F} \) be a family of vector-valued functions with two vector inputs. The problem of
searching to complete (SIF) low-rank matrix is to find an interaction function \( f^* \) such that

\[
f^* = \arg\min_{f \in F} \sum_{(i,j) \in \Omega} \mathcal{M} \left( f(u^*_i, v^*_j)^T w^*, O_{ij} \right) \quad \text{s.t.} \quad \|U^*, V^*, w^*\| = \arg\min_{U,V,w} F(U, V, w), \tag{3}
\]

where \( u^*_i \) (resp. \( v^*_j \)) is the \( i \)th column of \( U^* \) (resp. \( j \)th column of \( V^* \)).

Similar to other AutoML problems (such as auto-sklearn \cite{Falkner18} and NAS \cite{Bender20, Gao20}), SIF is a bi-level optimization problem \cite{Bengio18}. On the top level, a good architecture \( f \) is searched based on the validation set. On the lower level, we find the model parameters using \( F \) on the training set. Due to the nature of bi-level optimization, AutoML problems are difficult to solve in general.

In the following, we show how to design an expressive search space (Section 3.2), propose an efficient search algorithm (Section 3.3), and extend the proposed method to tensor data (Section 3.4).

### 3.2 Designing a Search Space

Because of the powerful approximation capability of deep networks \cite{Zoph16}, NCF \cite{Graepel16b} and Deep&Wide \cite{Chen16} use a MLP as \( f \). SIF then becomes searching a suitable MLP from the family \( F \) based on the validation set, where both MLP’s architectures and weights can be searched. However, a direct search of this MLP can be expensive and difficult, since determining its architecture is already an extremely time-consuming problem as observed in the NAS literature \cite{Zoph18, Li20}. Thus, as in Section 2.2, it is preferable to use a simple but expressive search space that exploits domain-specific knowledge from experts.

Notice that the operations in Table 1 can be either (i) a possibly nonlinear function operating on individual elements; or (ii) operators that operate on the whole input vector. Inspired by previous attempts that divide the NAS search space into blocks \cite{Zoph18, Li20}, we propose to first search for a nonlinear transform on each single element, and then combine these element-wise operations on the vector level. Let \( \mathcal{O} \) be an operator selected from \{multi, plus, min, max, concat\}, \( g(\beta; x) \in \mathbb{R} \) be a simple nonlinear function with input \( \beta \in \mathbb{R} \) and \( x \). We construct a search space \( F \) for \( \mathcal{O} \), where each \( f \) is expressed as:

\[
f(u_i, v_j) = \mathcal{O}(\tilde{u}_i, \tilde{v}_j) \text{ with } [\tilde{u}_i]_l = g([u_i]_l; p) \text{ and } [\tilde{v}_j]_l = g([v_j]_l; q), \tag{4}
\]

where \([u_i]_l\) (resp. \([v_j]_l\)) is the \( l \)th element of \( u_i \) (resp. \( v_j \)). In the sequel, we omit the convolution and outer product from \( \mathcal{O} \) (vector-wise operations) in \cite{Zoph18}, as they need significantly more computational time and have inferior performance than the rest (see Section 4.3). Besides, we parameterize \( g \) with a very small MLP with fixed architecture (single input, single output, five sigmoid hidden units) for element-wise level in \cite{Zoph18}, and the \( \ell_2 \)-norm of the weight is constrained to be no larger than 1.

This search space \( F \) meets the requirements for AutoML in Section 2.2. First, as it involves an extra nonlinear transformation, it contains operations that are more general than those designed by experts in Table 1. Such expressiveness leads to better performance than human-designed models in the experiments (Section 3.2). Second, the search space is much more constrained than of a general MLP mentioned above, as we only need to select an operation for \( \mathcal{O} \) and determine the weights for a small MLP fixed architecture (see Section 4.1).

![Figure 1: Representing the search space as a structured MLP.](image)

### 3.3 Efficient Search Algorithm

Usually, AutoML problems are expensive to search, as full model training is required. In this section, we propose an efficient algorithm, which only approximately trains the models, to search the space in an end-to-end and stochastic manner. Our algorithm is motivated by the recent success of differentiable architecture search \cite{Rudraraju20,Zoph18} and proximal algorithm \cite{Iguchi18}.

#### 3.3.1 Continuous Representation of the Space

Note that the search space introduced by \cite{Zoph18} is discrete, which is generally inefficient to conduct search. Motivated by differentiable search in NAS \cite{Rudraraju20,Zoph18}, we propose to relax the choices among
While SIF and DARTS both adopt (7) to approximate gradients, the search spaces are fundamentally different. DARTS searches connections in a cell of a deep network, but we search IFCs for CF. Besides, sparsity constraint is not considered in DARTS, SIF introduces $C$ with lazy proximal steps to select the proper operations. This not only makes SIF faster than DARTS, but also improves the search performance over DARTS. Finally, while there is no theoretical guarantee that SIF can converge to a locally optimal solution, as observed in [27][26], approximation gradients with (7) lead to good empirical solutions.

Proposition 3.2. $\prox_{C}(a) = \prox_{C_1}(\prox_{C_2}(a))$, where $C_1 = \{a \mid \|a\|_0 = 1\}$ and $C_2 = \{a \mid 0 \leq \alpha_k \leq 1\}$, i.e., $C = C_1 \cap C_2$.

In the AutoML literature, the most closely related work with the proposed Algorithm[1] is DARTS [26]. While SIF and DARTS both adopt (7) to approximate gradients, the search spaces are fundamentally different. DARTS searches connections in a cell of a deep network, but we search IFCs for CF. Besides, sparsity constraint is not considered in DARTS, SIF introduces $C$ with lazy proximal steps to select the proper operations. This not only makes SIF faster than DARTS, but also improves the search performance over DARTS. Finally, while there is no theoretical guarantee that SIF can converge to a locally optimal solution, as observed in [27][26], approximation gradients with (7) lead to good empirical solutions.

Algorithm 1 Searching Interaction Function (SIF) algorithm.

1: a search space $\mathcal{F}$ represented by the structured MLP (Figure[1]):
2: for epoch $t = 1, \ldots, T$ do
3: perform lazy-proximal step $a_t \leftarrow \prox_{\mathcal{F}}(a)$;
   sample a mini-batch on validation data set
4: update $a$ for vector-wise MLP by $a \leftarrow a - \epsilon \nabla_a H(T, S)$;
5: update $\mathbf{p}$ for element-wise MLP by $\mathbf{p} \leftarrow \mathbf{p} - \epsilon \nabla_\mathbf{p} H(T, S)$ (same for $q$);
   sample a mini-batch on training data set
6: update embeddings $T$ by stochastic gradient w.r.t. $F_a$;
7: end for
8: return searched interaction function (parameterized by $a$, $\mathbf{p}$ and $q$).
3.4 Extension to Tensor Data

As mentioned in Section 1, CF methods have also been used to handle tensor data. For example, low-rank matrix factorization is extended to tensor factorization, where two types of decomposition formats, i.e., CP and Tucker [23], are popularly used. These two methods are also based on the inner product. Besides, the factorization machine [33] is also recently extended to handle data cube [6]. These motivate us to extend the proposed SIF algorithm for tensor data. In the sequel, we focus on the 3-order tensor. Higher-order tensors can be handled in a similar way.

For tensors, we need to maintain three embedded vectors, \( u_i \), \( v_j \), and \( s_l \). First, we modify \( f \) to take three vectors as input and output another vector, and each candidate in search space (4) subsequently becomes \( f = O(\dot{u}_i, \dot{v}_j, \dot{s}_l) \), where \( \dot{u}_i \)'s are obtained from element-wise MLP from \( u_i \) (and similarly for \( \dot{v}_j \) and \( \dot{s}_l \)). However, \( O \) is no longer a single operation, as three vectors are involved. \( O \) enumerates all possible combinations from basic operations in the matrix case. For examples, if only \( \text{max} \) and \( \odot \) are allowed, then \( O \) contains \( \text{max}(u_i, v_j) \odot s_l, \text{max}(u_i, v_j), s_l \), \( u_i \odot \text{max}(v_j, s_l) \) and \( u_i \odot v_j \odot s_l \). With the above modifications, it is easy to see that the space can still be represented by a structured MLP similar to that in Figure 1. Moreover, the proposed Algorithm 1 can still be applied. Note that the search space is much larger for tensor than matrix.

4 Experiments

MovieLens (matrix data) and Youtube (tensor data) are used. These are benchmark data sets popularly used in the literature [29, 12, 25]. We uniformly and randomly select 50% of the ratings for training, 25% for validation and the rest for testing. Except for IFCs, other hyper-parameters are all tuned with grid search on the validation set.

The task is to predict missing ratings given the training data set. We use the squared loss for both \( M \) and \( \ell \). For performance evaluation, we use (i) the testing RMSE as in [29, 12]: \( \text{RMSE} = \sqrt{\frac{1}{\Omega} \sum_{(i,j) \in \Omega} (w^T f(u_i, v_j))^2} \), where \( f \) is the operation chosen by the algorithm, and \( w, u_i \)'s and \( v_j \)'s are parameters learned from the training set; and (ii) clock time (in seconds) as in [2, 26]. All codes are implemented in PyTorch, and run on a GPU cluster with eight Titan-XP GPUs.

4.1 Comparison with state-of-the-arts AutoML approaches

The following popular AutoML approaches are compared: (i) “Random”: Both operations and weights (for the small and fixed MLP) in the designed search space (in Section 3.2) are uniformly and randomly set (specifically, random search [4] is used). Following [41, 42], we use reinforcement learning (“RL”) [35] to search the designed space; (ii) “Bayes”: the designed search space is optimized by HyperOpt [5], which is a popular Bayesian optimization approach for hyperparameter tuning; and (iii) the proposed Algorithm 1 (denoted “SIF”) and its variant in which parameter \( S \) for IFCs are also optimized with training data (denoted “SIF(no-auto)”). Besides, using a MLP as a general approximator (“Gen-approx”), as described in Section 3.2, to approximate the search space is also compared. The MLP is updated with gradient descent [3] using the validation set. Since searching network architectures is expensive [41, 42], the structure of the MLP is fixed for Gen-approx.

Figure 2: Comparison of testing RMSEs between SIF and other AutoML approaches with different embedding dimensions. Gen-approx is slow with bad performance, thus is not run on Youtube.
Effectiveness. Testing RMSEs of the various AutoML approaches are shown in Figure 2. Note that MovieLens-10M is not tested as other methods (except SIF) are too slow (Figure 3). First, we can see that designing the search space with a general approximator is undesirable, as the performance of Gen-approx is worse than Random, RL and Bayes. SIF(no-auto) is worse than SIF as IFCs is purely search by the training set. Among all methods, the proposed SIF is the best. It can find good IFCs, leading to lower testing RMSEs than all other methods under different embedding dimensions.

Efficiency. Efficiency of the various AutoML approaches are compared in Figure 3. First, due to the large search space introduced by a general approximator, Gen-approx can be even slower than Random. Moreover, since the search space for tensor data is larger than that for matrix data, all algorithms become slower on Youtube. Besides, SIF is much faster than all the other methods and has lower testing RMSEs. The gap is larger on the Youtube dataset. Finally, SIF can find IFCs within 5 times of clock times from humans’ fine-tuning of existing CFs.

Searched interaction functions (IFCs). To explain why a lower RMSE can be achieved by the proposed method, we show the searched IFCs by various AutoML methods. Results on MovieLens-100K are shown in Figure 4(a). We can see that Random, RL and Bayes fail to pick the best operation identified by SIF. Besides, we also show in Figure 4(b) the searched nonlinear transformation for each element. We can see that SIF can find more complex transformations than the other AutoML methods.

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4.2 Comparison with State-of-the-Art CF Approaches

For matrix data: With the searched IFCs in Section 4.1, here we compare SIF with popular CF approaches. The following methods for matrix data are compared: (i) alternative gradient descent ("AltGrad") [24]: This is the most popular CF method, which is based on matrix factorization (i.e., inner product operation). We use gradient descent for optimization; (ii) factorization machine ("FM") [33]: This extends linear regression with matrix factorization to capture second-order interactions among features; (iii) Deep&Wide [8]: This is a recent CF method, which first embeds discrete features and then concatenates them for prediction; (iv) Neural collaborative filtering ("NCF") [15]: This is another recent CF method, which models the IFC by neural networks.

For tensor data: Deep&Wide and NCF can be easily extended to handle tensor data. Since the rank for the tensor is not uniquely defined, Thus, the following CF methods for tensor data are considered:
Two types of popularly used low-rank factorization of tensor are used, i.e., “CP” and “Tucker”, and gradient descent is used for optimization; “HOFM” [6]: a fast variant of FM, which can capture high-order interactions among features.

Figure 5: Comparison of testing RMSEs between SIF and other CF approaches with different embedding dimension.

Effectiveness. Comparison on the testing RMSEs is shown in Figure 5. First, as the embedding dimension gets larger, all methods gradually overfit and the testing RMSEs get higher. SIF(no-auto) is slightly better than the other CF approaches, which demonstrates the expressiveness of the designed search space. Finally, with the searched IFCs, SIF consistently obtains lower testing RMSEs than all other CF approaches.

Efficiency. As mentioned in [39], training algorithms are likely to have faster convergence if the hyperparameters can better capture properties in the data set. We show the training efficiency with the searched interactions vs human-designed CF methods in Figure 6. As can be seen, the searched IFC can be more efficiently trained, which further shows the superiority of searching IFCs from the data.

Figure 6: Comparison of the convergence between SIF (with searched IFC) and other CF methods when embedded dimension is 8. FM and HOFM are not shown as their code donot support a callback to record testing performance.

4.3 Comparison with Single Operation

To further demonstrate the need of AutoML and effectiveness of SIF, we show the performance of each single operation in Figure 7(a). It can be seen that while some operations can be better than others (e.g., plus is better than conv), there is no clear winner among all operations; and the best operation may depends on embedded dimensions as well. These verify the need of AutoML. Besides, SIF achieves consistently lower testing RMSEs than all single operations, and converges faster as well. Note that SIF in Figure 4(a) may not select the best single operation in Figure 7(a) due to the learned non-linear transformation (Figure 4(b)).

4.4 Comparison with DARTS

In Section 3.3, we have shown that DARTS and proximal algorithm (PA) are motivations to the proposed SIF. Here, we demonstrate that these two baseline algorithms are inferior to SIF. For PA, $\alpha$ is updated with $\alpha \leftarrow \text{prox}_c (\alpha - \epsilon \nabla \alpha (T, S))$, while the other steps are the same as Algorithm 1.
(a) Single operations. (b) SIF v.s DARTS. (c) SIF v.s DARTS.

Figure 7: Left: performance of each single operation on MovieLens-100K. Middle and right: comparison of standard proximal algorithm (PA), DARTS and SIF on MovieLens1M and Youtube.

MovieLens-100K is used and the embedding dimension is set as 8. The comparison is in Figures 7(b)-(c). We can see that, as explained in Section 3.3.2, standard PA algorithm which directly maintains a discrete indeed leads to poor performance. Besides, while all operations are activated for DARTS, only one single operation is activated for SIF when updating embeddings. This helps SIF to be much faster and better than DARTS.

5 Conclusion

In this paper, we propose an AutoML approach to search interaction functions for CF. The keys are an expressive search space, a continuous representation of the space, and an efficient algorithm which can jointly search interaction functions and update embedded vectors in a stochastic manner. Experimental results demonstrate that the proposed method is much more efficient than popular AutoML approaches, and also obtains much better learning performance than human-designed CF approaches.

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