**Differentiable Neural Input Search for Recommender Systems**

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**Abstract**

Latent factor models are the driving forces of the state-of-the-art recommender systems, with an important insight of vectorizing raw input features into dense embeddings. The dimensions of different feature embeddings are often set to a uniform value manually or through grid search, which may yield suboptimal model performance. Existing work applied heuristic methods or reinforcement learning to search for varying embedding dimensions. However, the embedding dimension per feature is rigidly chosen from a restricted set of candidates due to the scalability issue involved in the optimization process over a large search space. In this paper, we propose a differentiable neural input search algorithm towards learning more flexible dimensions of feature embeddings, namely a mixed dimension scheme, leading to better recommendation performance and lower memory cost. Our method can be seamlessly incorporated with various existing architectures of latent factor models for recommendation. We conduct experiments with 6 state-of-the-art model architectures on two typical recommendation tasks: Collaborative Filtering (CF) and Click-Through-Rate (CTR) prediction. The results demonstrate that our method achieves the best recommendation performance compared with 3 neural input search approaches over all the model architectures, and can reduce the number of embedding parameters by $2 \times$ and $20 \times$ on CF and CTR prediction, respectively.

**1 Introduction**

Most state-of-the-art recommender systems employ latent factor models that vectorize raw input features into dense embeddings. A key question often asked of feature embeddings is: “How should we determine the dimensions of feature embeddings?” The common practice is to set a uniform dimension for all the features, and treat the dimension as a hyperparameter that needs to be adjusted according to validation set. However, the manual search of a uniform embedding dimension can be computationally intensive and even result in suboptimal model performance, since a single dimension is not necessarily suitable for all the features. Intuitively, a larger dimension is needed for popular features that appear in most data samples, encouraging a higher model capacity to fit the related data samples \[20, 39\]. Likewise, less frequent features would rather be assigned with smaller dimensions to avoid overfitting on scarce data samples. As such, it is desirable to impose a mixed dimension scheme for different features towards better recommendation performance. Another notable fact is that embedding layers in industrial web-scale recommender systems \[10, 31\] account for the majority of model parameters and can consume hundreds of gigabytes of memory space. Replacing a uniform feature embedding dimension with varying dimensions is the key to remove redundant embedding weights for infrequent and less predictive features, leading to lower memory cost.

Some recent works \[15, 20\] have focused on searching for varying feature dimensions automatically, which is defined as the Neural Input Search (NIS) problem. Ginart et al. \[15\] proposed to use an empirical function to heuristically decide the embedding dimensions for different features according
to their frequencies of occurrence, where the empirical function involves several hyperparameters that need to be carefully tuned to yield a good search result. Joglekar et al. [20] proposed a reinforcement learning-based method for addressing the NIS problem. They first divided a base feature dimension equally into several blocks, and then applied reinforcement learning to produce decision sequences for different features on the selection of dimension blocks. These methods, however, restrict each feature dimension to be chosen from a small set of candidate dimensions that is explicitly predefined [20] or implicitly controlled by hyperparameters [15]. Although this restriction reduces search space and thereby improves computational efficiency, another question then arises: how to decide the candidate dimensions? Notably, a suboptimal set of candidate dimensions could result in a suboptimal search result that hurts model’s recommendation performance.

In this paper, we propose Differentiable Neural Input Search (DNIS) for approaching the NIS problem in a differentiable manner through gradient descent. Instead of searching over a predefined discrete set of candidate dimensions, DNIS relaxes the search space to be continuous and optimizes the selection for each feature dimension by descending model’s validation loss. More specifically, we introduce a soft selection layer between the embedding layer and the feature interaction layers of latent factor models. Each input feature embedding is fed into the soft selection layer to perform an element-wise multiplication with a scaling vector. The soft selection layer directly controls the significance of each dimension of the feature embedding, and it is essentially a part of model architecture which can be optimized according to model’s validation performance. We also propose a gradient normalization technique to keep the backpropagated gradients steady during the training of the soft selection layer. After training, we merge the soft selection layer with the feature embedding layer to prune redundant or less informative embedding dimensions per feature, leading to feature embeddings with a mixed dimension scheme. DNIS can be seamlessly applied to various existing architectures of latent factor models for recommendation. We conduct extensive experiments with different model architectures on the Collaborative Filtering (CF) task and the Click-Through-Rate (CTR) prediction task. The results demonstrate that our DNIS method achieves the best performance compared with the existing neural input search baselines over all the model architectures, and can increase parameter efficiency by pruning over $2\times$ and $20\times$ embedding weights for CF and CTR prediction, respectively.

The major contributions of this paper can be summarized as follows:

- We propose DNIS, a differentiable neural input search method to relax the NIS search space to be continuous, which allows searching for varying feature dimensions automatically in a differentiable manner with gradient descent.
- We introduce a soft selection layer to optimize the selection of embedding dimensions for different features. A gradient normalization technique is proposed to keep the backpropagated gradients steady during the training of the soft selection layer.
- Our method can be incorporated with various existing architectures of latent factor models to improve recommendation performance and reduce memory cost of embedding parameters.
- We conduct experiments with different model architectures on CF and CTR prediction tasks. The results demonstrate our DNIS method outperforms the existing NIS baselines in terms of recommendation performance, training efficiency and parameter size.

2 Differentiable Neural Input Search

2.1 Background

Latent factor models. We consider a recommender system involving $M$ feature fields (e.g., user ID, item ID, item price). Typically, $M$ is 2 (including user ID and item ID) in collaborative filtering (CF) problems, whereas in the context of click-through rate (CTR) prediction, $M$ is much larger than 2 to include more feature fields. Each categorical feature field consists of a collection of discrete features, while a numerical feature field contains one scalar feature. Let $\mathcal{F}$ denote the list of features over all the fields and the size of $\mathcal{F}$ is $N$. For the $i$-th feature in $\mathcal{F}$, its initial representation is a $N$-dimensional sparse vector $x_i$, where the $i$-th element is 1 (for discrete feature) or a scalar number (for scalar feature), and the others are 0s. Latent factor models generally consists of two parts: one feature embedding layer, followed by the feature interaction layers. Without loss of generality, the input instances to the latent factor model include several features belonging to the respective feature fields. The feature embedding layer transforms all the features in an input instance into dense
embedding vectors. Specifically, a sparsely encoded input feature vector $x_i \in \mathbb{R}^N$ is transformed into a $K$-dimensional embedding vector $e_i \in \mathbb{R}^K$ as follows:

$$e_i = E^T x_i \tag{1}$$

where $E \in \mathbb{R}^{N \times K}$ is known as the embedding matrix. The output of the feature embedding layer is the collection of dense embedding vectors for all the input features, which is denoted as $\mathbf{X}$. The feature interaction layers, which are designed to be different architectures, essentially compose a parameterized function $G$ that predicts the objective based on the collected dense feature embeddings $\mathbf{X}$ for the input instance. That is,

$$\hat{y} = G(\theta, \mathbf{X}) \tag{2}$$

where $\hat{y}$ is the model’s prediction, and $\theta$ denotes the set of parameters in the interaction layers. Prior works have developed various architectures for $G$, including the simple inner product function [36], and deep neural networks-based interaction functions [6, 8, 16, 19, 24]. Most of the proposed architectures for the interaction layers require all the feature embeddings to be in a uniform dimension.

**Neural architecture search.** Neural Architecture Search (NAS) has been proposed to automatically search for the best neural network architecture. To explore the space of neural architectures, different search strategies have been explored including random search [22], evolutionary methods [12, 29], Bayesian optimization [2, 11, 28], reinforcement learning [1, 40, 41], and gradient-based methods [3, 25, 38]. Since being proposed in [1, 41], NAS has achieved remarkable performance in various tasks such as image classification [35, 42], semantic segmentation [4] and object detection [42]. However, most of these researches have focused on searching for optimal network structures automatically, while little attention has been paid to the design of the input component. This is because the input component in visual tasks is already given in the form of floating point values of image pixels. As for recommender systems, an input component based on the embedding layer is deliberately developed to transform raw features (e.g., discrete user identifiers) into dense embeddings. In this paper, we focus on the problem of neural input search, which can be considered as NAS on the input component (i.e., the embedding layer) of recommender systems.

### 2.2 Search Space and Problem

**Search space.** The key idea of neural input search is to use embeddings with mixed dimensions to represent different features. To formulate feature embeddings with different dimensions, we adopt the representation for sparse vectors (with a base dimension $K$). Specifically, for each feature, we maintain a dimension index vector $d$ which contains ordered locations of the feature’s existing dimensions from the set $\{1, \cdots, K\}$, and an embedding value vector $v$ which stores embedding values in the respective existing dimensions. The conversion from the index and value vectors of a feature into the $K$-dimensional embedding vector $e$ is straightforward. Note that $e$ corresponds to a row in the embedding matrix $E$. Figure 1a gives an example of $d_i$, $v_i$ and $e_i$ for the $i$-th feature in $F$.

The size of $d$ varies among different features to enforce a mixed dimension scheme. Formally, given the feature set $F$, we define the mixed dimension scheme $D = \{d_1, \cdots, d_N\}$ to be the collection of dimension index vectors for all the features in $F$. We use $D$ to denote the search space of the mixed dimension scheme $D$ for $F$, which includes $2^{NK}$ possible choices. Besides, we denote by $V = \{v_1, \cdots, v_N\}$ the set of the embedding value vectors for all the features in $F$. Then we can derive the embedding matrix $E$ with $D$ and $V$ to make use of the feature interaction layers.

**Problem formulation.** Let $\Theta = \{\theta, V\}$ be the set of trainable model parameters, and $L_{\text{train}}$ and $L_{\text{val}}$ are model’s training loss and validation loss, respectively. The two losses are determined by both the mixed dimension scheme $D$, and the trainable parameters $\Theta$. The goal of neural input search
is to find a mixed dimension scheme $D \in \mathcal{D}$ that minimizes the validation loss $L_{\text{val}}(\Theta^*, D)$, where the parameters $\Theta^*$ given any mixed dimension scheme are obtained by minimizing the training loss. This can be formulated as:

$$\min_{D \in \mathcal{D}} L_{\text{val}}(\Theta^*(D), D)$$

$$\text{s.t. } \Theta^*(D) = \arg\min_{\hat{\Theta}} L_{\text{train}}(\hat{\Theta}, D) \quad (3)$$

The above problem formulation is actually consistent with hyperparameter optimization in a broader scope [13][27][33], since the mixed dimension scheme $D$ can be considered as model hyperparameters to be determined according to model’s validation performance. However, the main difference is that the search space $\mathcal{D}$ in our problem is much larger than the search space of conventional hyperparameter optimization problems.

2.3 Feature Blocking

Feature blocking has been a novel ingredient used in the existing neural input search methods [15][20] to facilitate the reduction of search space. The intuition behind is that features with similar frequencies could be grouped into a block sharing the same embedding dimension. Following the existing works, we first employ feature blocking to control the search space of the mixed dimension scheme. We sort all the features in $\mathcal{F}$ in the descending order of frequency (i.e., the number of feature occurrences in the training instances). Let $\eta_f$ denote the frequency of feature $f \in \mathcal{F}$. We can obtain a sorted list of features $\hat{\mathcal{F}} = \{f_1, f_2, \cdots, f_N\}$ such that $\eta_{f_i} \geq \eta_{f_j}$ for any $i < j$. We then separate $\hat{\mathcal{F}}$ into $L$ blocks, where the features in a block share the same dimension index vector $d$. We denote by $\hat{D}$ the mixed dimension scheme after feature blocking. Then the length of the mixed dimension scheme $|\hat{D}|$ becomes $L$, and the search space size is reduced from $2^{NK}$ to $2^{LK}$ accordingly, where $L \ll N$.

2.4 Continuous Relaxation and Differentiable Optimization

**Continuous relaxation.** After feature blocking, in order to optimize the mixed dimension scheme $\hat{D}$, we first transform $\hat{D}$ into a binary dimension indicator matrix $\hat{\mathcal{D}} \in \mathbb{R}^{L \times K}$, where each element in $\hat{\mathcal{D}}$ is either 1 or 0 indicating the existence of the corresponding embedding dimension according to $\hat{D}$. We then introduce a soft selection layer to relax the search space of $\hat{\mathcal{D}}$ to be continuous. The soft selection layer is essentially a numerical matrix $\alpha \in \mathbb{R}^{L \times K}$, where each element in $\alpha$ satisfies: $0 \leq \alpha_{l,k} \leq 1$. That is, each binary choice $\hat{D}_{l,k}$ (the existence of the $k$-th embedding dimension in the $l$-th feature block) in $\hat{D}$, is relaxed to be a continuous variable $\alpha_{l,k}$ within the range of $[0, 1]$. We insert the soft selection layer between the feature embedding layer and interaction layers in the latent factor model, as illustrated in Figure 1b. Given $\alpha$ and the embedding matrix $E$, the output embedding $\hat{e}_i$ of a feature $f_i$ in the $l$-th block produced by the bottom two layers can be computed as follows:

$$\hat{e}_i = e_i \odot \alpha_{l,s} \quad (4)$$

where $\alpha_{l,s}$ is the $l$-th row in $\alpha$, and $\odot$ is the element-wise product. By applying Equation (4) to all the input features, we can obtain the output feature embeddings $\hat{X}$. Next, we supply $\hat{X}$ to the feature interaction layers for final prediction as specified in Equation (2). Note that $\alpha$ is used to softly select the dimensions of feature embeddings during model training, and the discrete mixed dimension scheme $D$ will be derived after training.

**Differentiable optimization.** Now that we relax the mixed dimension scheme $\hat{\mathcal{D}}$ (after feature blocking) via the soft selection layer $\alpha$, our problem stated in Equation (3) can be transformed into:

$$\min_{\alpha} L_{\text{val}}(\Theta^*(\alpha), \alpha)$$

$$\text{s.t. } \Theta^*(\alpha) = \arg\min_{\hat{\Theta}} L_{\text{train}}(\hat{\Theta}, \alpha) \land \alpha_{k,j} \in [0, 1] \quad (5)$$

where that $\Theta = \{\theta, E\}$ represents model parameters in both the embedding layer and interaction layers. Equation (5) essentially defines a bi-level optimization problem [9], which has been studied in differentiable NAS [25] and gradient-based hyperparameter optimization [5][13][33]. Basically, $\alpha$ and $\Theta$ are respectively treated as the upper-level and lower-level variables to be optimized in an interleaving way. To deal with the expensive optimization of $\Theta$, we follow the common practice that approximates $\Theta^*(\alpha)$ by adapting $\Theta$ using a single training step:

$$\Theta^*(\alpha) \approx \Theta - \xi \nabla_{\Theta} L_{\text{train}}(\hat{\Theta}, \alpha) \quad (6)$$
Algorithm 1: DNIS - Differentiable Neural Input Search

1: **Input:** training dataset, validation dataset.
2: **Output:** mixed dimension scheme $D$, embedding values $V$, interaction function parameters $\theta$.
3: Sort features into $\mathcal{F}$ and divide them into $L$ blocks;
4: Initialize the soft selection layer $\alpha$ to be an all-one matrix, and randomly initialize $\Theta$;
5: while not converged do
6:  Update trainable parameters $\Theta$ by descending $\nabla_{\Theta} \mathcal{L}_{\text{train}}(\Theta, \alpha)$;
7:  Calculate the gradients of $\alpha$ as: $-\xi \nabla_{\alpha} \mathcal{L}_{\text{train}}(\Theta, \alpha) \cdot \nabla_{\alpha} \mathcal{L}_{\text{val}}(\Theta', \alpha) + \nabla_{\alpha} \mathcal{L}_{\text{val}}(\Theta', \alpha)$; // (set $\xi = 0$ if using first-order approximation)
8:  Perform Equation (8) to normalize the gradients in $\alpha$;
9:  Update $\alpha$ by descending the gradients, and then clip its values into the range of $[0, 1]$;
10: end
11: Calculate the output embedding matrix $E$ using $\alpha$ and $\tilde{E}$ according to Equation (4);
12: Prune $E$ into a sparse matrix $E'$ following Equation (9);
13: Derive the mixed dimension scheme $D$ and embedding values $V$ with $E'$;

where $\xi$ is the learning rate for one-step update of model parameters $\Theta$. Then we can optimize $\alpha$ based on the following gradient:

$$
\nabla_{\alpha} \mathcal{L}_{\text{val}}(\Theta - \xi \nabla_{\Theta} \mathcal{L}_{\text{train}}(\Theta, \alpha), \alpha) \\
= -\xi \nabla_{\alpha} \mathcal{L}_{\text{train}}(\Theta, \alpha) \cdot \nabla_{\alpha} \mathcal{L}_{\text{val}}(\Theta', \alpha) + \nabla_{\alpha} \mathcal{L}_{\text{val}}(\Theta', \alpha)
$$

where $\Theta' = \Theta - \xi \nabla_{\Theta} \mathcal{L}_{\text{train}}(\Theta, \alpha)$ denotes the model parameters after one-step update. Equation (7) can be solved efficiently using the existing deep learning libraries that allow automatic differentiation, such as Pytorch [32]. The second-order derivative term in Equation (7) can be omitted to further improve computational efficiency considering $\xi$ to be near zero, which is called the first-order approximation. In this paper, we adopt the first-order approximation in DNIS by default since we find the final performance is similar with and without the approximation. Algorithm 1 (line 5-10) summarizes the bi-level optimization procedure for solving Equation (5).

**Gradient normalization.** During the optimization of $\alpha$ by the gradient $\nabla_{\alpha} \mathcal{L}_{\text{val}}(\Theta', \alpha)$, we propose a gradient normalization technique to normalize the row-wise gradients of $\alpha$ over each training batch:

$$
g_{\text{norm}}(\alpha_{ts}) = \frac{g(\alpha_{ts})}{\sum_{k=1}^{K} |g(\alpha_{t,k})|/K + \epsilon_{g}}, \quad k \in [1, K]
$$

where $g$ and $g_{\text{norm}}$ denote the gradients before and after normalization respectively, and $\epsilon_{g}$ is a small value (e.g., 1e-7) to avoid numerical overflow. The consideration is that the magnitude of the gradients of $\alpha_{ts}$ varies a lot over feature blocks due to the significant difference in feature frequency. By normalizing the gradients for each block, we can apply a single learning rate to different rows of $\alpha$ during optimization. Otherwise, a single learning rate shared by different feature blocks may easily fall short in optimizing all the rows of $\alpha$.

### 2.5 Deriving Feature Embeddings in Mixed Dimensions

After optimization, we have the learned parameters for $\theta$, $E$ and $\alpha$. This allows us to derive the discrete mixed dimension scheme $D$. Specifically, for feature $f_{l}$ in the $l$-th block, we can compute its output embedding $\tilde{E}_{l}$ with $e_{l}$ and $\alpha_{l,ts}$ following Equation (4). By merging the embedding layer with the soft selection layer, we collect the output embeddings for all the features in $\mathcal{F}$ and form an output embedding matrix $\tilde{E} \in \mathbb{R}^{N \times K}$. We then prune non-informative embedding dimensions in $\tilde{E}$ as follows:

$$
\tilde{E}_{i,j} = \begin{cases} 
0, & \text{if } |\tilde{E}_{i,j}| < \epsilon \\
E_{i,j}, & \text{otherwise}
\end{cases}
$$

where $\epsilon$ is a threshold that can be manually tuned according to the requirements on model performance and computational resources. The pruned output embedding matrix $\tilde{E}$ is sparse and can be used to derive the discrete mixed dimension scheme $D$ and the embedding value vectors $V$ for $\mathcal{F}$ accordingly.

**Relation to network pruning.** Network pruning, as one kind of model compression techniques, improves the efficiency of over-parameterized deep neural networks by removing redundant neurons or connections without damaging model performance [7] [14] [26]. Recent works of network
Table 1: Statistics of the datasets.

| Dataset   | Task Type       | Instance#       | Field# | Feature# |
|-----------|-----------------|-----------------|--------|----------|
| Movielens | Rating Prediction | 20,000,263     | 2      | 165,771  |
| Criteo    | CTR Prediction   | 45,840,617      | 39     | 2,086,936 |

pruning \cite{17, 23, 30} generally performed iterative pruning and finetuning over certain pretrained over-parameterized deep network. Instead of simply removing redundant weights, our proposed method DNIS optimizes feature embeddings with the gradients from the validation set, and only prunes non-informative embedding dimensions and their values in one shot after model training. This also avoids manually tuning thresholds and regularization terms per iteration. We have conducted experiments to compare the performance of DNIS and network pruning methods in Section 3.4.

3 Experiments

3.1 Experimental Settings

Datasets. We used two benchmark datasets Movielens \cite{18} and Criteo \cite{21} for collaborative filtering (CF) and click-through rate (CTR) prediction tasks, respectively. For each dataset, we randomly split the instances by 8:1:1 to obtain the training, validation and test sets. The statistics of the two datasets are summarized in Table 1.

(1) Movielens consists of more than 20 million user ratings ranging from 1 to 5 on different movies.
(2) Criteo is a popular industry benchmark dataset for CTR prediction, which contains 13 numerical feature fields and 26 categorical feature fields. Each label indicates whether a user has clicked the corresponding item.

Evaluation metrics. We adopt MSE (mean squared error) for rating prediction in CF, and use AUC (Area Under the ROC Curve) and Logloss (cross entropy) for CTR prediction. In addition to model performance, we also report the parameter size and the search cost of each method.

Comparison methods. We compare our DNIS method with the following three approaches.

• Grid Search. This is the traditional approach to searching for a uniform embedding dimension. In our experiments, we searched 16 groups of dimensions, ranging from 4 to 64 with a stride of 4.

• Random Search. Random search has been recognized as a strong baseline for NAS problems \cite{25}. When random searching a mixed dimension scheme, we applied the same feature blocking as we did for DNIS. Following the intuition that high-frequency features desire larger numbers of dimensions, we generated 16 random descending sequences as the search space of the mixed dimension scheme for each model and report the best results.

• MDE (Mixed Dimension Embeddings \cite{15}). This method performs feature blocking and applies a heuristic scheme where the number of dimensions per feature block is proportional to some fractional power of its frequency. We tested 16 groups of hyperparameters settings as suggested in the original paper and report the best results.

For DNIS, we show its performance before and after the dimension pruning in Equation (9), and report the storage size of the pruned sparse matrix \( E' \) using COO format of sparse matrix \cite{37}. We show the results with different compression rates (CR), i.e., the division of unpruned embedding parameter size by the pruned size.

Implementation details. We implement our method using Pytorch \cite{32}. We apply Adam optimizer with the learning rate of 0.001 for model parameters \( \Theta \) and that of 0.01 for soft selection layer parameters \( \alpha \). The mini-batch size is set to 4096 and the uniform base dimension \( K \) is set to 64 for all the models. We apply the same blocking scheme for random search, MDE and DNIS for a fair comparison. The default numbers of feature blocks \( L \) is set to 10 and 6 for Movielens and Criteo datasets, respectively. We employ various latent factor models: MF, MLP \cite{19} and NeuMF \cite{19} for the CF task, and FM \cite{36}, Wide&Deep \cite{6}, DeepFM \cite{16} for the CTR prediction, where the configuration of latent factor models are the same over different methods. Besides, we exploit early-stopping for all the methods according to the change of validation loss during model training. All the experiments were performed using NVIDIA GeForce RTX 2080Ti GPUs.

3.2 Comparison Results

Table 2 and Table 3 show the comparison results of different NIS methods on CF and CTR prediction tasks, respectively. First, we can see that DNIS achieves the best prediction performance over
Table 2: Comparison between DNIS and baselines on the CF task using Movielens dataset. We also report the storage size of the derived feature embeddings and the training time per method. For DNIS, we show its results with and w/o different compression rates (CR), i.e., the ratio of the embedding parameter size w/o pruning to that after pruning.

| Search Methods | Params (M) | MF | Time | Cost | MSE  | MLP | Time | Cost | MSE  | NeuMF | Time | Cost | MSE  |
|----------------|------------|----|------|------|------|-----|------|------|------|-------|------|------|------|
| Grid Search    | 33         | 16h| 0.622|      |      | 35  | 8h   | 0.640|      | 61    | 4h   | 0.625|      |
| Random Search  | 33         | 16h| 0.6153|     |      | 22  | 4h   | 0.631|      | 30    | 2h   | 0.6238|      |
| MDE            | 35         | 24h| 0.6138|     |      | 35  | 5h   | 0.632|      | 27    | 3h   | 0.6249|      |
| DNIS (unpruned)| 37         | 1h | 0.6096|     |      | 36  | 1h   | 0.6255|     | 72    | 1h   | 0.6146|      |
| DNIS (CR = 2) | 21         | 1h | 0.6126|     |      | 20  | 1h   | 0.6303|     | 40    | 1h   | 0.6169|      |
| DNIS (CR = 2.5)| 17        | 1h | 0.6167|     |      | 17  | 1h   | 0.6361|     | 32    | 1h   | 0.6213|      |

Table 3: Comparison between DNIS and baselines on the CTR prediction task using Criteo dataset.

| Search Methods | Params (M) | FM | Time Cost | AUC | Logloss | Wide&Deep | Time Cost | AUC | Logloss | DeepFM | Time Cost | AUC | Logloss |
|----------------|------------|----|-----------|-----|---------|-----------|-----------|-----|---------|--------|-----------|-----|---------|
| Grid Search    | 441        | 16h| 0.7987    | 0.4525|         | 254       | 16h       | 0.8079| 0.4435| 382    | 14h       | 0.8080| 0.4435 |
| Random Search  | 73         | 12h| 0.7997    | 0.4518|         | 105       | 16h       | 0.8084| 0.4434| 105    | 12h       | 0.8084| 0.4434 |
| MDE            | 397        | 16h| 0.7986    | 0.4530|         | 196       | 16h       | 0.8076| 0.4439| 396    | 16h       | 0.8077| 0.4438 |
| DNIS (unpruned)| 441        | 3h | 0.8004    | 0.4510|         | 395       | 3h        | 0.8088| 0.4429| 416    | 3h        | 0.8090| 0.4427 |
| DNIS (CR = 20) | 26        | 3h | 0.8004    | 0.4510|         | 29        | 3h        | 0.8087| 0.4430| 29     | 3h        | 0.8088| 0.4428 |
| DNIS (CR = 30) | 17        | 3h | 0.8004    | 0.4510|         | 19        | 3h        | 0.8085| 0.4432| 20     | 3h        | 0.8086| 0.4430 |

all the model architectures for both tasks. It is worth noticing that the improvement on training efficiency ranges from 2× to over 10×. The results confirms that DNIS is able to learn discriminative feature embeddings with significantly higher efficiency than the existing search methods. Second, DNIS with dimension pruning achieves competitive or better performance than baselines, and can yield a significant reduction on model parameter size. For example, DNIS with a pruning rate (PR) of 2 outperforms all the baselines on Movielens, and yet reaches the minimal parameter size. The advantages of DNIS with the CR of 20 and 30 are more significant on Criteo. We observe that DNIS can achieve a higher CR on Criteo than Movielens without sacrificing prediction performance. This is because the distribution of feature frequency on Criteo is severely skewed, leading to a significantly large number of redundant dimensions for low-frequency features. Third, among all the baselines, MDE performs the best on Movielens and Random Search performs the best on Criteo, while Grid Search gets the worst results on both tasks. This verifies the importance of applying mixed dimension embeddings to latent factor models. Note that all of the three baselines have searched over 16 groups of feature dimensions, and their time costs are slightly different due to the early-stopping of model training. Fourth, we find that MF achieves better prediction performance on the CF task than the other two model architectures. The reason may be the overfitting problem of MLP and NeuMF that results in poor generalization. Besides, DeepFM show the best results on the CTR prediction task, suggesting that the ensemble of DNN and FM is beneficial to improving CTR prediction accuracy.

3.3 Hyperparameter Investigation

We investigate the effects of two important hyperparameters $K$ and $L$ in DNIS. Figure 2A shows the performance change of MF w.r.t. different settings of $K$. We can see that increasing $K$ is beneficial to reducing MSE. This is because a larger $K$ allows a larger search space that could improve the representations of high-frequency features by giving more embedding dimensions. Besides, we observe a marginal decrease in performance gain. Specifically, the MSE is reduced by 0.005 when $K$ increases from 64 to 128, whereas the MSE reduction is merely 0.001 when $K$ changes from 512 to 1024. This implies that $K$ may have exceeded the largest number of dimensions required by all the features, leading to minor improvements. Figure 2B shows the effects of the number of feature blocks $L$. We find that increasing $L$ improves the prediction performance of DNIS, and the performance improvement decreases as $L$ becomes larger. This is because dividing features into more blocks facilitates a finer-grained control on the embedding dimensions of different features, leading to more flexible mixed dimension schemes. Since both $K$ and $L$ affect the computation complexity of DNIS, we suggest to choose reasonably large values for $K$ and $L$ to balance the computational efficiency and predictive performance based on the application requirements.
Figure 2: Effects of hyperparameters on the performance of DNIS. We report the MSE results of MF on MovieLens dataset w.r.t. different base embedding dimensions $K$ and feature block numbers $L$.

Figure 3: (a) The distribution of trained parameters $\alpha$ of the soft selection layer. Here we show the result of MF on MovieLens dataset, where $L$ is set to 10. (b) The joint distribution plot of feature embedding dimensions and feature frequencies after dimension pruning. (c) Comparison of DNIS and network pruning performance over different pruning rates.

3.4 Analysis on DNIS Results

We first study the learned feature dimensions of DNIS through the learned soft selection layer $\alpha$ and feature embedding dimensions after dimension pruning. Figure 3a depicts the distributions of the trained parameters in $\alpha$ for the 10 feature blocks on MovieLens. Recall that the blocks are sorted in the descending order of feature frequency. It can be seen that the learned parameters in $\alpha$ for the feature blocks with lower frequencies converge to smaller values, indicating that lower-frequency features tend to be represented by smaller numbers of embedding dimensions. Figure 3b provides the number of embedding dimensions per feature after dimension pruning. The results show that features with higher frequencies end up with more embedding dimensions, whereas the dimensions are more likely to be pruned for low-frequency features. Nevertheless, there is no strong correlation between the derived embedding dimension and the feature frequency. Note that the embedding dimensions for low-frequency features scatter over a long range of numbers. This is consistent with the inferior performance of MDE which directly determines the number of feature embedding dimensions according to the frequency.

We further compare DNIS with network pruning method [17]. For illustration purpose, we provide the results of the FM model on Criteo dataset. Figure 3c shows the performance of two methods on different pruning rates (i.e., the ratio of pruned embedding values). DNIS achieves better AUC and Logloss results than network pruning over all the pruning rates. This is because DNIS optimizes feature embeddings with the gradients from the validation set, which benefits the selection of predictive dimensions, instead of simply removing redundant weights in the embeddings.

4 Conclusion

In this paper, we introduced Differentiable Neural Input Search (DNIS), which searches for a mixed dimension scheme for different features adaptively from data. Instead of selecting from a predefined discrete set of candidate dimension schemes, DNIS is able to optimize embedding dimensions in a continuous search space with gradient descent. The key idea is to develop a soft dimension selection layer that controls the significance of each embedding dimension, and can be optimized with model’s validation performance through gradient descent. We show that DNIS can be seamlessly incorporated with various existing latent factor models for recommendation. We conduct extensive experiments on collaborative filtering and click-through rate prediction tasks, where DNIS outperforms the existing NIS baselines in terms of recommendation performance, training efficiency and parameter size.
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