

Differentiable Neural Input Search for Recommender Systems

Weiyu Cheng, Yanyan Shen, Linpeng Huang

Shanghai Jiao Tong University
{weiyu_cheng, shenyy, lphuang}@sjtu.edu.cn

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 same value empirically, which limits the predictive performance of latent factor models. Existing works have proposed heuristic or reinforcement learning-based methods to search for mixed feature embedding dimensions. For efficiency concern, these methods typically choose embedding dimensions from a restricted set of candidate dimensions. However, this restriction will hurt the flexibility of dimension selection, leading to suboptimal performance of search results.

In this paper, we propose Differentiable Neural Input Search (DNIS), a method that searches for mixed feature embedding dimensions in a more flexible space through continuous relaxation and differentiable optimization. The key idea is to introduce a soft selection layer that controls the significance of each embedding dimension, and optimize this layer according to model’s validation performance. DNIS is model-agnostic and thus can be seamlessly incorporated with existing latent factor models for recommendation. We conduct experiments with various architectures of latent factor models on three public real-world datasets for rating prediction, Click-Through-Rate (CTR) prediction, and top-k item recommendation. The results demonstrate that our method achieves the best predictive performance compared with existing neural input search approaches with fewer embedding parameters and less time cost.

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 tuned with time-consuming grid search on a validation set. However, a uniform embedding dimension is not necessarily suitable for different features. Intuitively, predictive and popular features that appear in a large number of data samples usually deserve a high embedding dimension, which encourages a high model capacity to fit these data samples [Joglekar et al. 2020; Zhao et al. 2020]. Likewise, less predictive and infrequent features

would rather be assigned with lower embedding 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 account for the majority of model parameters and can consume hundreds of gigabytes of memory space [Park et al. 2018; Covington, Adams, and Sargin 2016]. Replacing a uniform feature embedding dimension with varying dimensions can help to remove redundant embedding weights and significantly reduce memory and storage costs for model parameters.

Some recent works [Ginart et al. 2019; Joglekar et al. 2020] have focused on searching for mixed feature embedding dimensions automatically, which is defined as the *Neural Input Search (NIS)* problem. There are two existing approaches to dealing with NIS: *heuristic-based* and *reinforcement learning-based*. The heuristic-based approach [Ginart et al. 2019] designs an empirical function to determine the embedding dimensions for different features according to their frequencies of occurrence (also called popularity). The empirical function involves several hyperparameters that need to be manually tuned to yield a good result. The reinforcement learning-based approach [Joglekar et al. 2020] first divides a base dimension space equally into several blocks, and then applies reinforcement learning to generate decision sequences on the selection of dimension blocks for different features. These methods, however, restrict each feature embedding dimension to be chosen from a small set of candidate dimensions that is explicitly predefined [Joglekar et al. 2020] or implicitly controlled by hyperparameters [Ginart et al. 2019]. 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) to address 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 of embedding dimensions 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 solve the problem of high variance of gradients when optimizing the soft selection layer. After training, we employ a fine-grained pruning procedure by merging the soft selection layer with the feature embedding layer, which yields a fine-grained mixed embedding dimension scheme for different features. DNIS can be seamlessly applied to various existing architectures of latent factor models for recommendation. We conduct extensive experiments with six existing architectures of latent factor model on three public real-world datasets for rating prediction, Click-Through-Rate (CTR) prediction, and top-k item recommendation tasks. The results demonstrate that the proposed method achieves the best predictive performance compared with existing NIS methods with fewer embedding parameters and less time cost.

The major contributions of this paper are summarized as follows:

- We propose DNIS, a method that addresses the NIS problem in a differentiable manner by relaxing the embedding dimension search space to be continuous and optimizing the selection of dimensions with gradient descent.
- We propose a gradient normalization technique to deal with the high variance of gradients during optimizing the soft selection layer, and further design a fine-grained pruning procedure through layer merging to produce a fine-grained mixed embedding dimension scheme for different features.
- The proposed method is model-agnostic, and thus can be incorporated with various existing architectures of latent factor models to improve recommendation performance and reduce the size of embedding parameters.
- We conduct experiments with different model architectures on real-world datasets for three typical recommendation tasks: rating prediction, CTR prediction, and top-k item recommendation. The results demonstrate DNIS achieves the best overall result compared with existing NIS methods in terms of recommendation performance, embedding parameter size and training time cost.

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 CTR prediction, M is usually 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 \mathbf{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 $\mathbf{x}_i \in \mathbb{R}^N$ is transformed into a K -dimensional embedding vector $\mathbf{e}_i \in \mathbb{R}^K$ as follows:

$$\mathbf{e}_i = \mathbf{E}^\top \mathbf{x}_i \quad (1)$$

where $\mathbf{E} \in \mathbb{R}^{N \times K}$ 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 \mathcal{G} that predicts the objective based on the collected dense feature embeddings \mathbf{X} for the input instance. That is,

$$\hat{y} = \mathcal{G}(\boldsymbol{\theta}, \mathbf{X}) \quad (2)$$

where \hat{y} is the model’s prediction, and $\boldsymbol{\theta}$ denotes the set of parameters in the interaction layers. Prior works have developed various architectures for \mathcal{G} , including the simple inner product function [Rendle 2010], and deep neural networks-based interaction functions [He et al. 2017; Cheng et al. 2018; Lian et al. 2018; Cheng et al. 2016; Guo et al. 2017]. 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 [Li and Talwalkar 2019], evolutionary methods [Elsken, Metzen, and Hutter 2019; Miller, Todd, and Hegde 1989; Real et al. 2017], Bayesian optimization [Bergstra, Yamins, and Cox 2013; Domhan, Springenberg, and Hutter 2015; Mendoza et al. 2016], reinforcement learning [Baker et al. 2017; Zhong et al. 2018; Zoph and Le 2017], and gradient-based methods [Cai, Zhu, and Han 2019; Liu, Simonyan, and Yang 2019; Xie et al. 2019]. Since being proposed in [Baker et al. 2017; Zoph and Le 2017], NAS has achieved remarkable performance in various tasks such as image classification [Real et al. 2019; Zoph et al. 2018], semantic segmentation [Chen et al. 2018] and object detection [Zoph et al. 2018]. 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,

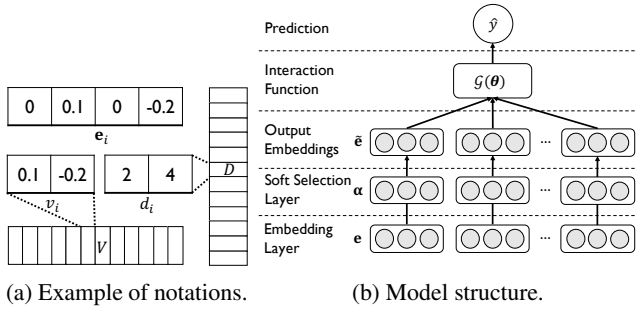


Figure 1: A demonstration of notations and model structure.

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 $\{1, \dots, K\}$, 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. Figure 1a gives an example of d_i , v_i and e_i for the i -th feature in \mathcal{F} . Note that e corresponds to a row in the embedding matrix \mathbf{E} .

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

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

$$\begin{aligned} \min_{D \in \mathcal{D}} \quad & \mathcal{L}_{val}(\Theta^*(D), D) \\ \text{s.t.} \quad & \Theta^*(D) = \underset{\Theta}{\operatorname{argmin}} \mathcal{L}_{train}(\Theta, D) \end{aligned} \quad (3)$$

The above problem formulation is actually consistent with hyperparameter optimization in a broader scope [Maclaurin, Duvenaud, and Adams 2015; Pedregosa 2016; Franceschi et al. 2018], 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 [Joglekar et al. 2020; Ginart et al. 2019] 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 η_f denote the frequency of feature $f \in \mathcal{F}$. We can obtain a sorted list of features $\tilde{\mathcal{F}} = [f_1, f_2, \dots, f_N]$ such that $\eta_{f_i} \geq \eta_{f_j}$ for any $i < j$. We then separate $\tilde{\mathcal{F}}$ into L blocks, where the features in a block share the same dimension index vector d . We denote by \tilde{D} the mixed dimension scheme after feature blocking. Then the length of the mixed dimension scheme $|\tilde{D}|$ 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 \tilde{D} , we first transform \tilde{D} into a binary *dimension indicator matrix* $\tilde{\mathbf{D}} \in \mathbb{R}^{L \times K}$, where each element in $\tilde{\mathbf{D}}$ is either 1 or 0 indicating the existence of the corresponding embedding dimension according to \tilde{D} . We then introduce a *soft selection layer* to relax the search space of $\tilde{\mathbf{D}}$ to be continuous. The soft selection layer is essentially a numerical matrix $\alpha \in \mathbb{R}^{L \times K}$, where each element in α satisfies: $0 \leq \alpha_{l,k} \leq 1$. That is, each binary choice $\tilde{\mathbf{D}}_{l,k}$ (the existence of the k -th embedding dimension in the l -th feature block) in $\tilde{\mathbf{D}}$ 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 α and the embedding matrix \mathbf{E} , the output embedding \tilde{e}_i of a feature f_i in the l -th block produced by the bottom two layers can be computed as follows:

$$\tilde{e}_i = e_i \odot \alpha_{l*} \quad (4)$$

where α_{l*} is the l -th row in α , and \odot is the element-wise product. By applying Equation (4) to all the input features, we can obtain the output feature embeddings \mathbf{X} . Next, we supply \mathbf{X} to the feature interaction layers for final prediction as specified in Equation (2). Note that α 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 $\tilde{\mathbf{D}}$ (after feature blocking) via the soft

selection layer α , our problem stated in Equation (3) can be transformed into:

$$\begin{aligned} \min_{\alpha} \quad & \mathcal{L}_{val}(\Theta^*(\alpha), \alpha) \\ \text{s.t.} \quad & \Theta^*(\alpha) = \arg\min_{\Theta} \mathcal{L}_{train}(\Theta, \alpha) \wedge \alpha_{k,j} \in [0, 1] \end{aligned} \quad (5)$$

where $\Theta = \{\theta, \mathbf{E}\}$ represents model parameters in both the embedding layer and interaction layers. Equation 5 essentially defines a bi-level optimization problem [Colson, Marcotte, and Savard 2007], which has been studied in differentiable NAS [Liu, Simonyan, and Yang 2019] and gradient-based hyperparameter optimization [Chen et al. 2019; Franceschi et al. 2018; Pedregosa 2016]. Basically, α and Θ 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 Θ , we follow the common practice that approximates $\Theta^*(\alpha)$ by adapting Θ using a single training step:

$$\Theta^*(\alpha) \approx \Theta - \xi \nabla_{\Theta} \mathcal{L}_{train}(\Theta, \alpha) \quad (6)$$

where ξ is the learning rate for one-step update of model parameters Θ . Then we can optimize α based on the following gradient:

$$\begin{aligned} & \nabla_{\alpha} \mathcal{L}_{val}(\Theta - \xi \nabla_{\Theta} \mathcal{L}_{train}(\Theta, \alpha), \alpha) \\ = & \nabla_{\alpha} \mathcal{L}_{val}(\Theta', \alpha) - \xi \nabla_{\alpha, \Theta}^2 \mathcal{L}_{train}(\Theta, \alpha) \cdot \nabla_{\alpha} \mathcal{L}_{val}(\Theta', \alpha) \end{aligned} \quad (7)$$

where $\Theta' = \Theta - \xi \nabla_{\Theta} \mathcal{L}_{train}(\Theta, \alpha)$ 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 [Paszke et al. 2019]. The second-order derivative term in Equation (7) can be omitted to further improve computational efficiency considering ξ to be near zero, which is called the *first-order approximation*. Algorithm 1 (line 5-10) summarizes the bi-level optimization procedure for solving Equation (5).

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

$$\mathbf{g}_{norm}(\alpha_{l*}) = \frac{\mathbf{g}(\alpha_{l*})}{\sum_{k=1}^K |\mathbf{g}(\alpha_{l,k})| / K + \epsilon_{\mathbf{g}}}, \quad k \in [1, K] \quad (8)$$

where \mathbf{g} and \mathbf{g}_{norm} denote the gradients before and after normalization respectively, and $\epsilon_{\mathbf{g}}$ is a small value (e.g., $1e-7$) to avoid numerical overflow. Here we use row-wise gradient normalization to deal with the high variance of the gradients of α during backpropagation. More specifically, $\mathbf{g}(\alpha_{l*})$ of a high-frequency feature block can be several orders of magnitude larger than that of a low-frequency feature block due to their difference on the number of related data samples. By normalizing the gradients for each block, we can apply the same learning rate to different rows of α during optimization. Otherwise, a single learning rate shared by different feature blocks will fail to optimize most rows of α .

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

After optimization, we have the learned parameters for θ, \mathbf{E} and α . A straightforward way to derive the discrete mixed dimension scheme D is to prune non-informative embedding dimensions in the soft selection layer α . Here we employ a fine-grained pruning procedure through layer merging. Specifically, for feature f_i in the l -th block, we can compute its output embedding $\tilde{\mathbf{e}}_i$ with \mathbf{e}_i and α_{l*} following Equation (4). We collect the output embeddings $\tilde{\mathbf{e}}_i$ for all the features in \mathcal{F} and form an output embedding matrix $\tilde{\mathbf{E}} \in \mathbb{R}^{N \times K}$. We then prune non-informative embedding dimensions in $\tilde{\mathbf{E}}$ as follows:

$$\tilde{\mathbf{E}}_{i,j} = \begin{cases} 0, & \text{if } |\tilde{\mathbf{E}}_{i,j}| < \epsilon \\ \tilde{\mathbf{E}}_{i,j}, & \text{otherwise} \end{cases} \quad (9)$$

where ϵ is a threshold that can be manually tuned according to the requirements on model performance and parameter size. The pruned output embedding matrix $\tilde{\mathbf{E}}$ is sparse and can be used to derive the discrete mixed dimension scheme D and the embedding value vectors V for \mathcal{F} accordingly. With fine-grained pruning, the derived embedding dimensions can be different even for features in the same feature block, resulting in a more flexible mixed dimension scheme. **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 [Cheng et al. 2017; Liu et al. 2019; Frankle and Carbin 2019]. Recent works of network pruning [Han et al. 2015; Molchanov et al. 2017; Li et al.

Table 1: Statistics of the datasets.

Dataset	Instance#	Field#	Feature#
Movielens-20M	20,000,263	2	165,771
Criteo	45,840,617	39	2,086,936
Movielens-1M	1,000,209	2	9,746

2017] 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 conduct 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-20M [Harper and Konstan 2016] and Criteo [Labs 2014] for rating prediction and CTR prediction tasks, respectively. For each dataset, we randomly split the instances by 8:1:1 to obtain the training, validation and test sets. Besides, we also conduct experiments on Movielens-1M dataset [Harper and Konstan 2016] to compare with NIS-ME [Joglekar et al. 2020] for top-k item recommendation task. The statistics of the three datasets are summarized in Table 1.

(1) **Movielens-20M** is a CF dataset containing more than 20 million user ratings ranging from 1 to 5 on 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.

(3) **Movielens-1M** is a CF dataset containing over one million user ratings ranging from 1 to 5 on movies.

Evaluation metrics. We adopt MSE (mean squared error) for rating prediction task, and use AUC (Area Under the ROC Curve) and Logloss for CTR prediction task. In addition to predictive performance, we also report the embedding parameter size and the overall time cost of each method. When comparing with NIS-ME, we provide Recall, MRR (mean reciprocal rank) and NDCG results for top-k recommendation.

Comparison methods. We compare our DNIS method with the following four 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 [Liu, Simonyan, and Yang 2019]. 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 [Ginart et al. 2019]). 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.

- **NIS-ME** (Neural Input Search with Multi-size Embedding [Joglekar et al. 2020]). This method uses reinforcement learning to find optimal embedding dimensions for different features within a given memory budget. Since the implementation is not available, we follow the same experimental settings as detailed in [Joglekar et al. 2020]) and report the results of our method for comparison.

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 \mathbf{E}' using COO format of sparse matrix [Virtanen et al. 2020]. We provide 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 [Paszke et al. 2019]. We apply Adam optimizer with the learning rate of 0.001 for model parameters Θ and that of 0.01 for soft selection layer parameters α . 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. 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 [He et al. 2017] and NeuMF [He et al. 2017] for rating prediction, and FM [Rendle 2010], Wide&Deep [Cheng et al. 2016], DeepFM [Guo et al. 2017] for CTR prediction, where the configuration of latent factor models are the same over different methods for a fair comparison. 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 rating prediction and CTR prediction tasks, respectively. First, we can see that DNIS achieves the best prediction performance over all the model architectures for both tasks. It is worth noticing that the time cost of DNIS is reduced by $2\times$ to over $10\times$ compared with the baselines. 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 embedding parameter size. For example, DNIS with the CR 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. Besides, 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

Table 2: Comparison between DNIS and baselines on the rating prediction task using Movielens-20M 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 division of unpruned embedding parameter size by the pruned size.

Search Methods	MF			MLP			NeuMF		
	Params (M)	Time Cost	MSE	Params (M)	Time Cost	MSE	Params (M)	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	0.6361	30	2h	<u>0.6238</u>
MDE	35	24h	<u>0.6138</u>	35	5h	<u>0.6312</u>	27	3h	0.6249
DNIS (unpruned)	37	1h	0.6096	36	1h	0.6255	72	1h	0.6146
DNIS ($CR = 2$)	21	1h	<u>0.6126</u>	20	1h	<u>0.6303</u>	40	1h	<u>0.6169</u>
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	FM				Wide&Deep				DeepFM			
	Params (M)	Time Cost	AUC	Logloss	Params (M)	Time Cost	AUC	Logloss	Params (M)	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	<u>0.7997</u>	<u>0.4518</u>	105	16h	0.8084	<u>0.4434</u>	105	12h	0.8084	<u>0.4434</u>
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

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. Fourth, we find that MF achieves better prediction performance on the rating prediction 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.

Table 4 shows the performance of DNIS and NIS-ME with respect to base embedding dimension K and embedding parameter size for top-k item recommendation. From the results, we can see that DNIS achieves the best performance on most metrics (on average, the relative improvement over NIS-ME on Recall, MRR, and NDCG are 5.3%, 7.2%, and 2.7%, respectively). This indicates the effectiveness of DNIS by searching for the optimal mixed dimension scheme in a differentiable manner. Besides, NIS-ME shows consistent improvements over NIS-SE, admitting the benefit of replacing single embedding dimension with mixed dimensions.

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

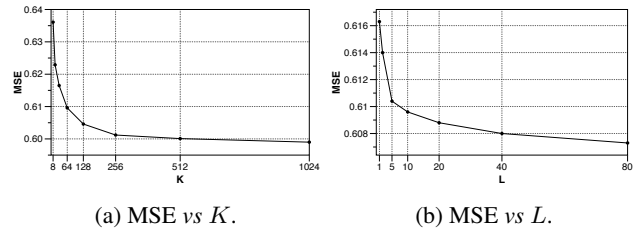
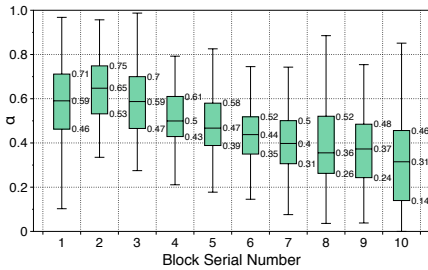


Figure 2: Effects of hyperparameters on the performance of DNIS. We report the MSE results of MF on Movielens-20M dataset w.r.t. different base embedding dimensions K and feature block numbers L .

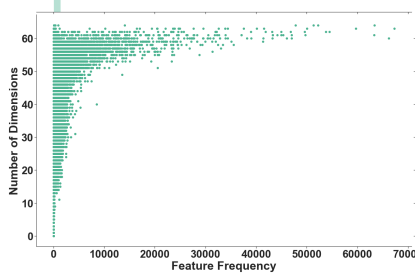
larger K allows a larger search space that could improve the representations of high-frequency features by giving more embedding dimensions. Besides, we observe a marginal decrease in performance gain. Specifically, the MSE is reduced by 0.005 when K increases from 64 to 128, whereas the MSE reduction 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

Table 4: Comparison between DNIS and NIS-ME on Movielens-1M dataset. NIS-SE is a variant of NIS-ME method with a shared number of embedding dimension. Here we use the results of the original paper [Joglekar et al. 2020].

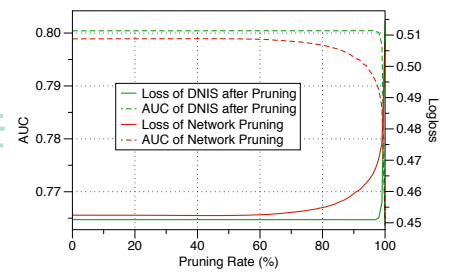
Model	K	#Params	Recall@1	Recall@5	@Recall@10	MRR@5	MRR@10	NDCG@5	NDCG@10
NIS-SE	16	390k	9.32	35.70	<u>55.31</u>	18.22	20.83	22.43	28.63
NIS-ME	16	390k	<u>9.41</u>	35.90	55.68	<u>18.31</u>	<u>20.95</u>	<u>22.60</u>	28.93
DNIS ($CR = 2$)	16	390k	11.39	<u>35.79</u>	51.74	19.82	21.93	23.77	<u>28.90</u>
NIS-SE	16	195k	8.42	31.37	<u>50.30</u>	15.04	17.57	19.59	25.12
NIS-ME	16	195k	<u>8.57</u>	<u>33.29</u>	52.91	<u>16.78</u>	<u>19.37</u>	<u>20.83</u>	<u>27.15</u>
DNIS ($CR = 4$)	16	195k	11.15	33.34	49.62	18.74	20.88	22.35	27.58
NIS-SE	32	780k	9.90	37.50	<u>55.69</u>	19.18	21.60	23.70	29.58
NIS-ME	32	780k	<u>10.40</u>	38.66	57.02	<u>19.59</u>	<u>22.18</u>	<u>24.28</u>	<u>30.60</u>
DNIS ($CR = 2$)	32	780k	13.01	<u>38.26</u>	55.43	21.83	24.12	25.89	31.45
NIS-SE	32	390k	9.79	34.84	<u>53.23</u>	17.85	20.26	22.00	27.91
NIS-ME	32	390k	<u>10.19</u>	37.44	56.62	<u>19.56</u>	<u>22.09</u>	<u>23.98</u>	30.14
DNIS ($CR = 4$)	32	390k	11.95	<u>35.98</u>	51.92	20.27	22.39	24.15	<u>29.30</u>



(a) α in different feature blocks.



(b) Embedding dimension vs η_f .



(c) Performance vs Pruning rates.

Figure 3: (a) The distribution of trained parameters α 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.

performance based on the application requirements.

3.4 Analysis on DNIS Results

We first study the learned feature dimensions of DNIS through the learned soft selection layer α and feature embedding dimensions after dimension pruning. Figure 3a depicts the distributions of the trained parameters in α for the 10 feature blocks on Movielens. Recall that the blocks are sorted in the descending order of feature frequency. We can see that the learned parameters in α 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 correlation between embedding dimensions and feature frequency after dimension pruning. The results show that features with high frequencies end up with high embedding dimensions, whereas the dimensions are more likely to be pruned for low-frequency features. Nevertheless, there is no linear relationship 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 embedding dimensions of features according to their frequency.

We further compare DNIS with network pruning method [Han et al. 2015]. For illustration purpose, we pro-

vide 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 weights). From the result, 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 propose Differentiable Neural Input Search (DNIS), a method that searches for mixed features embedding dimensions in a differentiable manner through gradient descent. The key idea of DNIS is to introduce a soft selection layer that controls the significance of each embedding dimension, and optimize this layer according to model’s validation performance. We propose a gradient normalization technique and a fine-grained pruning procedure in DNIS to produce a flexible mixed embedding dimension scheme for different features. The proposed method is model-agnostic, and can be incorporated with various existing architectures of latent factor models. We conduct experiments on three public real-world recommendation datasets. The results show that DNIS achieves the best predictive performance compared with existing neural input search methods with fewer embedding parameters and less time cost.

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