FiBiNet++:Improving FiBiNet by Greatly Reducing Model Size for CTR Prediction

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Abstract

Click-Through Rate(CTR) estimation has become one of the most fundamental tasks in many real-world applications and various deep models have been proposed to resolve this problem. Some research has proved that FiBiNet is one of the best performance models and outperforms all other models on Avazu dataset. However, the large model size of FiBiNet hinders its wider applications. In this paper, we propose a novel FiBiNet++ model to redesign FiBiNet's model structure, which greatly reduces model size while further improves its performance. Extensive experiments on three public datasets show that FiBiNet++ effectively reduces non-embedding model parameters of FiBiNet by 12x to 16x on three datasets and has comparable model size with DNN model which is the smallest one among deep CTR models.On the other hand, FiBiNet++ leads to significant performance improvements compared to state-of-theart CTR methods, including FiBiNet. The source code is in https://github.com/recommendation-algorithm/FiBiNet.

 $\label{eq:ccs} \textit{CCS Concepts: } \bullet \textbf{Information systems} \rightarrow \textbf{Recommender systems}.$

Keywords: Recommender System; Click-Through Rate; Feature Importance

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1 Introduction

Click-through rate (CTR) prediction plays important role in personalized advertising and recommender systems. In recent years, a series of deep CTR models have been proposed to resolve this problem such as Wide & Deep Learning[11],

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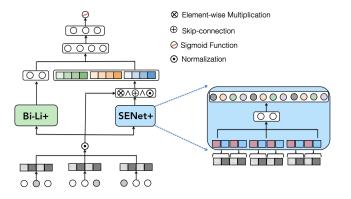


Figure 1. The Framework of FiBiNet++

DeepFM[2],DCN[8],xDeepFM [4] AutoInt[7],DCN v2[9] and FiBiNet[3]. Specifically, Wide & Deep Learning[11] jointly trains wide linear models and deep neural networks to combine the benefits of memorization and generalization for recommender systems. DeepFM[2] replaces the wide part of Wide & Deep model with FM and shares the feature embedding between the FM and deep component. Some works explicitly introduce high-order feature interactions by subnetwork.For example,Deep & Cross Network (DCN)[8] and DCN v2[9]efficiently capture feature interactions of bounded degrees in an explicit fashion. The eXtreme Deep Factorization Machine (xDeepFM) [4] also models the low-order and high-order feature interactions in an explicit way by proposing a novel Compressed Interaction Network (CIN) part. Similarly, AutoInt[7] proposes a multi-head self-attentive neural network with residual connections to explicitly model the feature interactions in the low-dimensional space.FiBiNet[3] dynamically learns the importance of features via the Squeeze-Excitation network (SENET) and feature interactions via bi-linear function. Though many models have been proposed, seldom works fairly compares these model's performance. FuxiCTR[13] performs open benchmarking for CTR prediction and presents a rigorous comparison of various models in a reproducible manner. This works runs over 7,000 experiments for more than 12,000 GPU hours in total to reevaluate 24 existing models on multiple datasets. Experimental results[13]show that FiBiNet is one of the best performance models and outperforms all other 23 models on Avazu dataset, which is one of the most popular real-world benchmarks for CTR model evaluation.

However, we argue in this paper that FiBiNet has too much model parameters, which mainly come from the design shortcoming of bi-linear module and hinder its wider applications in many real life CTR scenes. Our works aims to redesign the model structure to greatly reduce model size while maintaining or even improving its performance. In this paper, we propose a novel FiBiNet++ model to address these challenges as shown in Figure 1. First, we reconstruct the model structure by removing the bi-linear module on SENet and linear part in FiBiNet, which directly reduces large amount of parameters. Second, we upgrade bi-linear function into bi-linear+ module by changing the hadamard product to inner product and bringing a compression MLP layer into it, which further reduces model size. Finally, we introduce feature normalization and the upgraded SENet+ module to enhance model performance. Extensive experiments are conducted on three public real-world datasets and experimental results show that FiBiNet++ provides orders of magnitude improvement in model size while improving the quality of the model compared with FiBiNet. We summarize our major contributions as below:

- 1. The proposed FiBiNet++ greatly reduces non-embedding model size of FiBiNet by 12x to 16x on three datasets and has comparable model size with DNN model which is the smallest one among deep CTR models.
- FiBiNet++ yields remarkable improvements compared to state-of-the-art models on three real-world datasets, including FiBiNet.

2 PRELIMINARIES

Deep learning models are widely used in industrial recommendation systems, such as DNN [12], DCN [8],DeepFM [2] and FiBiNet[3]. Among them, DNN model [12] is almost the simplest one and is always used as a sub-component in most current DNN ranking systems[2–4, 8]. It contains three components:feature embedding,MLP and prediction layer.In this section, we introduce the DNN model and the optimization objective of CTR prediction task.

2.1 Feature Embeddding

As all we know, features in CTR tasks usually can be segregated into the following two groups:

1. Categorical features. This type of feature is common and the one-hot representation may produce very sparse features. We map one-hot representation to dense, low-dimensional embedding vectors suitable for complex transformation. We can obtain feature embedding \mathbf{v}_i for one-hot vector \mathbf{x}_i via:

$$\mathbf{v}_i = \mathbf{W}_e \mathbf{x}_i \in \mathbb{R}^{1 \times d} \tag{1}$$

where $\mathbf{W}_e \in \mathbb{R}^{n \times d}$ is the embedding matrix of n features and d is the dimension of field embedding.

2. Numerical features. We map the feature field into an embedding vector as follows:

$$\mathbf{v}_i = \mathbf{e}_i \mathbf{x}_i \in \mathbb{R}^{1 \times d} \tag{2}$$

where $\mathbf{e}_i \in \mathbb{R}^{1 \times d}$ is an embedding vector for field i with size d, and \mathbf{x}_i is a scalar value which means the actual value of that numerical feature. Some big numerical values will dominate the parameter updating procedure during model training and we normalized \mathbf{x}_i into [0,1] via min-max normalization technique before multiplying it into \mathbf{e}_i to avoid this:

$$\mathbf{x}_i = \frac{\mathbf{x}_i - \mathbf{x}_{min}}{\mathbf{x}_{max} - \mathbf{x}_{min}} \tag{3}$$

2.2 MLP and Prediction Layer

To learn high-order feature interactions, multiple feed-forward layers are stacked on the concatenation of dense features represented as $\mathbf{H}_0 = concat[\mathbf{v}_1, \mathbf{v}_2, ..., \mathbf{v}_f]$, here f denotes fields number. Then, the feed forward process of MLP is:

$$\mathbf{H}_{l} = ReLU(\mathbf{W}_{l}\mathbf{H}_{l-1} + \beta_{l}) \tag{4}$$

where l is the depth and ReLU is the activation function. \mathbf{W}_l , β_l , \mathbf{H}_l are weighting matrix, bias and output of the l-th layer. The prediction layer is put on the last layer of multiple feed-forward networks,and the model's output is:

$$\hat{y} = \delta(\mathbf{w}_0 + \sum_{i=1}^n \mathbf{w}_i \mathbf{x}_i)$$
 (5)

where $\hat{y} \in (0, 1)$ is the predicted value of CTR, $\delta(\cdot)$ is the sigmoid function, n is the size of feed-forward layer, \mathbf{x}_i is the bit value of feed-forward layer and \mathbf{w}_i is the learned weight for each bit value.

2.3 Optimization Objective

For binary classifications, the loss function of CTR prediction is the log loss:

$$\mathcal{L} = -\frac{1}{N} \sum_{i=1}^{N} y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)$$
 (6)

where *N* is the total number of training instances, y_i is the ground truth of *i*-th instance and \hat{y}_i is the predicted CTR.

3 Our Proposed Model

The architecture of the proposed FiBiNet++ is shown in Figure 1.We argue that current structure of FiBiNet ,especially bi-linear function,leads to large amount of unnecessary parameters. Therefore, the bi-linear function on SENet module in original FiBiNet is removed and only left branch of bi-linear function is kept. In addition, the linear part of FiBiNet helps its good performance while we find it's beneficial to remove it from FiBiNet++ model. These two changes on network structure directly decrease model size and we will discuss this in detail in section 3.5.

As shown in Figure 1, the original feature embedding is first normalized before be sent to the following components. Then, biwith small size m. $\sigma_1(\cdot)$ is an identity function without nonlinear+ module models feature interactions and SENet+ module computes bit-wise feature importance. The outputs of two branches are concatenated as input of the following MLP layers.

3.1 Feature Normalization

Normalization techniques have been recognized as very effective component in deep learning and works[10] conducts a systematic study on the effect of widely used normalization schema to both feature embedding and MLP part in deep CTR model. Inspired by this work, we introduce feature normalization into FiBiNet++ to enhance model's training stability and performance as follows:

$$\mathbf{N}(\mathbf{V}) = concat[\mathbf{N}(\mathbf{v}_1), \mathbf{N}(\mathbf{v}_2), ..., \mathbf{N}(\mathbf{v}_f)] \in \mathbb{R}^{1 \times fd}$$
 (7)

where $N(\cdot)$ is layer normalization for numerical feature and batch normalization operation for categorical feature:

$$\mathbf{N}(\mathbf{v}_i) = \begin{cases} LN(\mathbf{v}_i) & if \quad \mathbf{x}_i \in S_c \\ \\ BN(\mathbf{v}_i) & if \quad \mathbf{x}_i \in S_n \end{cases}$$
(8)

here S_c is a set containing categorical features and S_n is a set of numerical features.

3.2 Bi-Linear+ Module

FiBiNet models interaction between feature \mathbf{x}_i and feature \mathbf{x}_i by bi-linear function which introduces an extra learned matrix **W** as follows:

$$\mathbf{p}_{i,j} = \mathbf{v}_i \circ \mathbf{W} \otimes \mathbf{v}_j \in \mathbb{R}^{1 \times d} \tag{9}$$

where \circ and \otimes denote inner product and element-wise hadamard product, respectively. The matrix W can be parameters to learn following one of the three options:'field all type','field each type' or 'field interaction type'. Though it's effective to model feature interactions via bi-linear function, we argue it is the hadamard product that brings large amount of unnecessary parameters. In order to effectively reduce model size, we upgrade bi-linear function into bi-linear+ module by following two methods. First, the hadamard product is replaced by another inner product as follows:

$$\mathbf{p}_{i,j} = \mathbf{v}_i \circ \mathbf{W} \circ \mathbf{v}_j \in \mathbb{R}^{1 \times 1} \tag{10}$$

It's easy to see the parameters of $\mathbf{p}_{i,j}$ decrease greatly from \mathbf{d} dimensional vector to 1 bit for each feature interaction. Suppose the input instance has f fields and we have the following vector after bi-linear feature interactions:

$$\mathbf{P} = concat[\mathbf{p}_{1,2}, \mathbf{p}_{1,3},, \mathbf{p}_{f-1,f}] \in \mathbb{R}^{1 \times \frac{f \times (f-1)}{2}}$$
 (11)

To further reduce parameter number, we introduce a compression MLP layer stacking on vector P as follows:

$$\mathbf{H}^{CML} = \sigma_1 \left(\mathbf{W}_1 \mathbf{P} \right) \in \mathbb{R}^{1 \times m} \tag{12}$$

where $\mathbf{W}_1 \in \mathbb{R}^{m \times \frac{f \times (f-1)}{2}}$ is a learning matrix of thin MLP layer linear transformation because we find model performance decreases when non-linear function is adopted here.

3.3 SENet+ Module

SENet module is comprised of three steps:squeeze, excitation and re-weight step and it is first proposed by FiBiNet in CTR prediction domain to dynamically compute the feature importance. We upgrade it into SENet+ to boost model performance in this paper.SENet+ module consists of four phases:squeeze, excitation, re-weight and fuse. Though our proposed SENet+ module has similar three phases just as original SENet does, each step is improved in order to enhance model performance.

Squeeze. SENet collects one bit information by mean pooling from each feature embedding as 'summary statistics'. However, we think more input information will benefit model performance. Therefore, we improve the original squeeze step by providing more useful information. Specifically, we first segment each normalized feature embedding $\mathbf{v}_i \in \mathbb{R}^{1 \times d}$ into g groups, which is a hyper-parameter, as follows:

$$\mathbf{v}_{i} = concat[\mathbf{v}_{i,1}, \mathbf{v}_{i,2}, \dots, \mathbf{v}_{i,a}]$$
 (13)

where $\mathbf{v}_{i,j} \in \mathbb{R}^{1 \times \frac{d}{g}}$ means information in the j-th group of the i-th feature. Let $\mathbf{k} = \frac{d}{g}$ denotes size of each group. Then, we select the max value $\mathbf{z}_{i,j}^{\textit{max}}$ and average pooling value $\mathbf{z}_{i,j}^{\textit{avg}}$ in $\mathbf{v}_{i,j}$ as representative information of the group as follows:

$$\mathbf{z}_{i,j}^{max} = \max_{t} \left\{ \mathbf{v}_{i,j}^{t} \right\}_{t=1}^{k}$$

$$\mathbf{z}_{i,j}^{avg} = \frac{1}{k} \sum_{t=1}^{k} \mathbf{v}_{i,j}^{t}$$
(14)

The concatenated representative information of each group forms the 'summary statistic' Z_i of feature embedding v_i :

$$\mathbf{Z}_{i} = concat[\mathbf{z}_{i,1}^{max}, \mathbf{z}_{i,1}^{avg}, \mathbf{z}_{i,2}^{max}, \mathbf{z}_{i,2}^{avg}, \dots, \mathbf{z}_{i,g}^{max}, \mathbf{z}_{i,g}^{avg}] \in \mathbb{R}^{1 \times 2g}$$
(15)

Finally, we can concatenate each feature's summary statistic as the input of SENet+ module:

$$\mathbf{Z} = concat[\mathbf{Z}_1, \mathbf{Z}_2, \dots, \mathbf{Z}_f] \in \mathbb{R}^{1 \times 2gf}$$
 (16)

Excitation. The excitation step in SENet computes each feature's weight according to statistic vector Z, which is a field-wise attention. However, we improve this step by changing the field-wise attention into a more fine-grained bit-wise attention. Similarly, we also use two full connected (FC) layers to learn the weights as follows:

$$\mathbf{A} = \sigma_3 \left(\mathbf{W}_3 \sigma_2 \left(\mathbf{W}_2 \mathbf{Z} \right) \right) \in \mathbb{R}^{1 \times fd} \tag{17}$$

where $\mathbf{W}_2 \in \mathbb{R}^{\frac{2gf}{r} \times 2gf}$ denotes learning parameters of first FC layer, which is a thin layer and r is reduction ratio. $\mathbf{W}_3 \in$ $\mathbb{R}^{fd imes rac{2gf}{r}}$ means learning parameters of second FC layer,which is a wider layer with size of fd. Here σ_2 (·) is ReLu (·) and σ_3 (·) is an identity function without non-linear transformation. In this way, each bit in input embedding can dynamically learns corresponding attention score provided by \mathbf{A} .

Re-Weight. Re-weight step does element-wise multiplication between the original field embedding and the learned attention scores as follows:

$$\mathbf{V}^{w} = \mathbf{A} \otimes \mathbf{N}(\mathbf{V}) \in \mathbb{R}^{1 \times fd}$$
 (18)

where \otimes is an element-wise multiplication between two vectors and N(V) denotes original embedding after normalization.

Fuse. An extra "fuse" step is introduced in order to better fuse the information contained both in original feature embedding and weighted embedding. Specifically, we first use skip-connection to merge two embedding as follows:

$$\mathbf{v}_{i}^{s} = \mathbf{v}_{i}^{o} \oplus \mathbf{v}_{i}^{w} \tag{19}$$

where \mathbf{v}_i^o donates the i-th normalized feature embedding, \mathbf{v}_i^w denotes embedding after re-weight step, \oplus is an element-wise addition operation. Then, another feature normalization is applied on feature embedding \mathbf{v}_i^s for a better representation:

$$\mathbf{v}_i^u = \mathbf{LN}(\mathbf{v}_i^s) \tag{20}$$

Note we adopt layer normalization here no matter what type of feature it belongs to,numerical or categorical feature. Finally, we concatenate all the fused embeddings as output of the SENet+ module:

$$\mathbf{V}^{SENet+} = concat[\mathbf{v}_1^u, \mathbf{v}_2^u, ..., \mathbf{v}_f^u] \in \mathbb{R}^{1 \times fd}$$
 (21)

3.4 Concatenation Layer

Let \mathbf{H}^{CML} denotes output of the compression MLP layer in bi-linear+ module and \mathbf{V}^{SENet+} denotes the weighted feature embedding of the SENet+ module,we can concatenate them to form the input of the following MLP layers:

$$\mathbf{H}_0 = concat[\mathbf{H}^{CML}, \mathbf{V}^{SENet+}] \tag{22}$$

The following procedure is same with what we describe in section 2.2 and section 2.3.

3.5 Discussion

In this section,we discuss the model size difference between FiBiNet and FiBiNet++.Note only non-embedding parameter is considered,which really demonstrates model complexity.

The major parameter of FiBiNet comes from two components:one is the connection between the first MLP layer and output of two bi-linear modules, and the other is the linear part. Suppose we denote h = 400 as size of first MLP layer, f = 50 as fields number, d = 10 as feature embedding size and t = 1 *million* as feature number. Therefore, the parameter

number in these two parts is nearly 10.8 millions:

$$\mathbf{T}^{FiBiNet} = \underbrace{\mathbf{f} \times (\mathbf{f} - \mathbf{1}) \times \mathbf{d} \times \mathbf{h}}_{MLP \ and \ bi-linear} + \underbrace{t}_{linear} = 10.8 \ millions \ (23)$$

For FiBiNet++, majority of model parameter comes from following three components:connection between the first MLP layer and embedding produced by SENet+ module(1-th part),connection between the first MLP layer and compression MLP layer(2-th part),and parameters between compression MLP layer and bi-linear feature interaction results(3-th part).Let m = 50 denote size of compression MLP layer.We have parameter number of these components as follows:

$$\mathbf{T}^{FiBiNet++} = \underbrace{\frac{\mathbf{f} \times \mathbf{d} \times \mathbf{h}}_{1-th \ part} + \underbrace{\frac{\mathbf{m} \times \mathbf{h}}_{2-th \ part}}_{2-th \ part} + \underbrace{\frac{\mathbf{f} \times (\mathbf{f} - \mathbf{1})}{2} \times \mathbf{m}}_{3-th \ part} = 0.28 \ millions$$
(24)

We can see that the above-mentioned methods to reduce model size greatly decrease model size from 10.8 millions to 0.28 millions, which is nearly 39x model compression. In addiction, the larger the fields number f is, the larger model compression ratio we can achieve.

4 Experimental Results

We conduct extensive experiments on three public datasets to validate the effectiveness of FiBiNet++. First,we describe the experimental settings and compare performance of FiBiNet++ with other state-of-the-art CTR models. Then, we compare the model size of FiBiNet++ with FiBiNet . Finally, we provide the hyper-parameter analyses of FiBiNet++.

4.1 Experiment Setup

Datasets. The following three datasets are used in our experiments:

Table 1. Statistics of the Evaluation Datasets

Datasets	#Instances	#fields	#features
Datasets	#IIIStances	#IICIUS	#Icatures
Criteo	45M	39	30M
Avazu	40.4M	24	9.5M
KDD12	194.6M	13	6M

- 1. **Criteo**¹ **Dataset**: As a very famous public real world display ad dataset with each ad display information and corresponding user click feedback, Criteo data set is widely used in many CTR model evaluation. There are 26 anonymous categorical fields and 13 continuous feature fields in Criteo data set.
- 2. **Avazu**² **Dataset:** The Avazu dataset consists of several days of ad click- through data which is ordered

¹Criteo http://labs.criteo.com/downloads/download-terabyte-click-logs/

²Avazu http://www.kaggle.com/c/avazu-ctr-prediction

Table 2. Overall performance (AUC) of different models on	L
three datasets	

	Avazu		Criteo		KDD12	
Model	AUC(%)	Paras.	AUC(%)	Paras.	AUC(%)	Paras.
FM	78.17	1.54M	78.97	1.0M	77.65	5.46M
DNN	78.67	<u>0.74M</u>	80.73	<u>0.48M</u>	79.54	<u>0.37M</u>
DeepFM	78.64	2.29M	80.58	1.48M	79.40	5.84M
xDeepFM	78.88	4.06M	80.64	4.90M	79.51	6.91M
DCN	78.68	0.75M	80.73	0.48M	79.58	0.37M
AutoInt+	78.62	0.77M	80.78	0.48M	79.69	0.38M
DCN v2	78.98	4.05M	80.88	0.65M	79.66	0.39M
FiBiNet	79.12	10.27M	80.73	7.25M	79.52	6.41M
FiBiNet++	79.15	0.81M	81.10	0.56M	79.98	0.40M
Improv.	+0.03	12.7x	+0.37	12.9x	+0.46	16x

chronologically. For each click data, there are 24 fields which indicate elements of a single ad impression.

3. **KDD12**³ **Dataset:** KDD12 dataset aims to predict the click-through rate of ads and the instances are derived from session logs of the Tencent proprietary search engine. There are 13 fields spanning from user id to ad position for a clicked data.

We randomly split instances by 8:1:1 for training , validation and test while Table 1 lists the statistics of the evaluation datasets.

Evaluation Metrics. AUC (Area Under ROC) is used as the evaluation metric in our experiments. This metric is very popular for binary classification tasks.Logloss (binary crossentropy loss) shows similar trend with AUC and we didn't present it because of the space limit.

Models for Comparisons. We compare the performance of the FM[6], DNN[12], DeepFM[2], DCN [8], AutoInt [7], DCN V2 [9], xDeepFM [4] and FiBiNet [3] models as baseline and all of which are discussed in Section 1.Results of some models such as LR [5], Wid&Deep [1] and AFM [11] are not presented in this paper, because more recent models like FiBiNet[3] and DCN-V2 [9] have outperformed these methods significantly as experiments in FuxiCTR [13] shows.

Implementation Details. We implement all the models with Tensorflow in our experiments. For optimization method, we use the Adam with a mini-batch size of 1024. We find different learning rate has great influence on some baseline's performance. Therefore, both 0.0001 and 0.001 learning rate are verified and the best results are reported as final performance for all baselines. We make the dimension of field embedding for all models to be a fixed value of 10 for Criteo dataset, 50 for Avazu dataset and 10 for KDD12 dataset. For models with DNN part, the depth of hidden layers is set to 3, the number of neurons per layer is 400, all activation

function are ReLU. In SENet+, the reduction ratio is set to 3 and group number is 2 as default settings. In Bi-linear+ module, we set the size of compression MLP layer as 50. For other models, we take the optimal settings from the original papers.

4.2 Performance Comparison

Table 2 shows the performance of different SOTA baselines and FiBiNet++. The experiments for FiBiNet++ and the baseline models are repeated 5 times by changing the random seeds and the averaged results are reported for fair comparison. The best results are in bold, and the best baseline results are underlined. From the experimental results, we mainly have the following observations:

- Our proposed FiBiNET++ model outperforms all the compared SOTA methods and achieves the best performance on all three benchmarks. Among all the baselines, FiBiNet, DCN v2 and AutoInt+ are best performance models on three datasets, respectively.
- 2. Compared with FiBiNet model, FiBiNet++ can achieve better performance on all datasets though it has much less parameters, which indicates that our proposed methods to enhance model performance are effective. Our experiments in Section 4.3 will show the model size comparison between two models.

4.3 Model Size Comparison

We compare the model size of different methods in Table 2.Note that the presented model parameters only contain the non-embedding parts of various models, which truly demonstrate the model complexity. We make the following observations from Table 2:

- Among all the baseline models,DNN is the smallest one while FiBiNet and xDeepFM are relatively complex models.FM and DeepFM also have much bigger model size compared with DNN because of the existence of linear part as original paper described.
- 2. As can be seen in Table 2 and Figure 3, FiBiNet++ provides orders of magnitude improvement in model size while improving the quality of the model compared with FiBiNet. Specifically,FiBiNet++ reduce model size of FiBiNet by 12.7x, 12.9x and 16x in terms of the number of parameters on three datasets, respectively, which demonstrates that our proposed methods to reduce model parameter in this paper are effective.Now FiBiNet++ has comparable model size with DNN model while outperforms all other models on three datasets at the same time.

4.4 Hyper-Parameters of FiBiNet++

In this section, we study hyper-parameter sensitivity of FiBiNet++. There are three hyper-parameters influencing the model performance: group number, reduction ratio in SENet+

³KDD12 https://www.kaggle.com/c/kddcup2012-track2

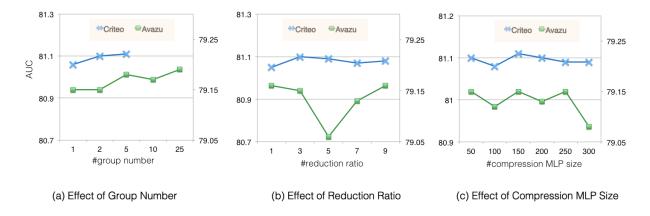


Figure 2. Effect of Hyper-Parameters

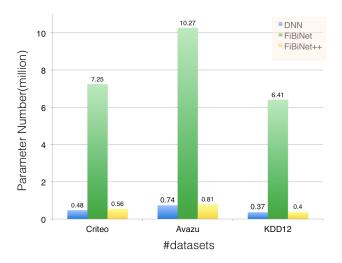


Figure 3. Comparison of Model Size

module and size of compression MLP layer in bi-linear+ module. The experiments are conducted on Criteo and Avazu datasets via changing one hyper-parameter while holding the other settings.

Group Number. Figure 2a shows the impact of group number of feature embedding on model performance. We can observe a slightly performance increase with the increase of group number, which indicates that more group number benefits model performance because we can input more useful information in feature embedding into SENet+ module. However, bigger group number will bring a wider input for SENET++ module and it will slow down the training speed.

Reduction Ratio. We conduct some experiments to adjust the reduction ratio in SENet+ module from 1 to 9 and Figure 2b shows the result. It can be seen that the performance is better if we set the reduction ratio to 3 or 9.

Size of Compression MLP Layer. The results in Figure 2c show the impact when we adjust the size of compression MLP layer in bi-linear+ module. We can observe that the performance begin to decrease when the size is set greater than 150,which demonstrates the thin layer is better and wider layer may bring more noise.

5 Conclusion

Some research shows that FiBiNet is one of the best performance CTR models. However, FiBiNet has too much model parameters that hinder its wider applications. In this paper, we propose FiBiNet++ model in order to greatly reduce the model size while improving the model performance. Experimental results show that FiBiNet++ provides orders of magnitude improvement in model size while improving the quality of the model compared with FiBiNet. It also outperforms other state-of-the-art models on three real-world datasets.

References

- [1] Heng-Tze Cheng, Levent Koc, Jeremiah Harmsen, Tal Shaked, Tushar Chandra, Hrishi Aradhye, Glen Anderson, Greg Corrado, Wei Chai, Mustafa Ispir, et al. 2016. Wide & deep learning for recommender systems. In Proceedings of the 1st workshop on deep learning for recommender systems. ACM, 7–10.
- [2] Huifeng Guo, Ruiming Tang, Yunming Ye, Zhenguo Li, and Xiuqiang He. 2017. DeepFM: a factorization-machine based neural network for CTR prediction. arXiv preprint arXiv:1703.04247 (2017).
- [3] Tongwen Huang, Zhiqi Zhang, and Junlin Zhang. 2019. FiBiNET: combining feature importance and bilinear feature interaction for clickthrough rate prediction. In Proceedings of the 13th ACM Conference on Recommender Systems, RecSys 2019, Copenhagen, Denmark, September 16-20, 2019. ACM, 169-177. https://doi.org/10.1145/3298689.3347043
- [4] Jianxun Lian, Xiaohuan Zhou, Fuzheng Zhang, Zhongxia Chen, Xing Xie, and Guangzhong Sun. 2018. xdeepfm: Combining explicit and implicit feature interactions for recommender systems. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. ACM, 1754–1763.
- [5] H. Brendan McMahan, Gary Holt, D. Sculley, Michael Young, Dietmar Ebner, Julian Grady, Lan Nie, Todd Phillips, Eugene Davydov, Daniel Golovin, and et al. 2013. Ad Click Prediction: A View from

- the Trenches. In *Proceedings of the 19th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (Chicago, Illinois, USA) (*KDD '13*). Association for Computing Machinery, New York, NY, USA, 1222–1230. https://doi.org/10.1145/2487575.2488200
- [6] Steffen Rendle. 2010. Factorization machines. In 2010 IEEE International Conference on Data Mining. IEEE, 995–1000.
- [7] Weiping Song, Chence Shi, Zhiping Xiao, Zhijian Duan, Yewen Xu, Ming Zhang, and Jian Tang. 2019. Autoint: Automatic feature interaction learning via self-attentive neural networks. In Proceedings of the 28th ACM International Conference on Information and Knowledge Management. 1161–1170.
- [8] Ruoxi Wang, Bin Fu, Gang Fu, and Mingliang Wang. 2017. Deep & cross network for ad click predictions. In *Proceedings of the ADKDD'17*. ACM, 12.
- [9] Ruoxi Wang, Rakesh Shivanna, Derek Zhiyuan Cheng, Sagar Jain, Dong Lin, Lichan Hong, and Ed H. Chi. 2021. DCN V2: Improved Deep & Cross Network and Practical Lessons for Web-scale Learning to

- Rank Systems. In WWW '21: The Web Conference 2021, Virtual Event / Ljubljana, Slovenia, April 19-23, 2021. 1785–1797.
- [10] Zhiqiang Wang, Qingyun She, Pengtao Zhang, and Junlin Zhang. 2020. Correct Normalization Matters: Understanding the Effect of Normalization On Deep Neural Network Models For Click-Through Rate Prediction. CoRR abs/2006.12753 (2020). arXiv:2006.12753 https://arxiv.org/abs/2006.12753
- [11] Jun Xiao, Hao Ye, Xiangnan He, Hanwang Zhang, Fei Wu, and Tat-Seng Chua. 2017. Attentional factorization machines: Learning the weight of feature interactions via attention networks. arXiv preprint arXiv:1708.04617 (2017).
- [12] Weinan Zhang, Tianming Du, and Jun Wang. 2016. Deep learning over multi-field categorical data. In European conference on information retrieval. Springer, 45–57.
- [13] Jieming Zhu, Jinyang Liu, Shuai Yang, Qi Zhang, and Xiuqiang He. 2020. FuxiCTR: An Open Benchmark for Click-Through Rate Prediction. ArXiv abs/2009.05794 (2020).