AutoFT: Automatic Fine-Tune for Parameters Transfer Learning in Click-Through Rate Prediction

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Abstract

Recommender systems are often asked to serve multiple recommendation scenarios or domains. Fine-tuning a pre-trained CTR model from source domains and adapting it to a target domain allows knowledge transferring. However, optimizing all the parameters of the pre-trained network may result in over-fitting if the target dataset is small and the number of parameters is large. This leads us to think of directly reusing parameters in the pre-trained model which represent more general features learned from multiple domains. However, the design of freezing or fine-tuning layers of parameters requires much manual effort since the decision highly depends on the pre-trained model and target instances. In this work, we propose an end-to-end transfer learning framework, called Automatic Fine-Tuning (AutoFT), for CTR prediction. AutoFT consists of a field-wise transfer policy and a layer-wise transfer policy. The field-wise transfer policy decides how the pre-trained embedding representations are frozen or fine-tuned based on the given instance from the target domain. The layer-wise transfer policy decides how the high-order feature representations are transferred layer by layer. Extensive experiments on two public benchmark datasets and one private industrial dataset demonstrate that AutoFT can significantly improve the performance of CTR prediction compared with state-of-the-art transferring approaches.

1 Introduction

Modern recommender systems are widely deployed to make precise personalized recommendations. In recommender systems, Click-Through Rate (CTR) prediction is a crucial task, which estimates the probability that a user will click on a recommended item under a specific context, so that the recommendation decisions can be made based on the predicted CTR values [Cheng et al., 2016; Guo et al., 2017; Qu et al., 2016; Qu et al., 2018; Lian et al., 2018; Wang et al., 2017]. Recommender systems are often asked to serve multiple recommendation scenarios. However, designing a unique CTR prediction model for each scenario (i.e., domain or task) is hard to achieve due to the limit of computing resource and human resource. Making it even worse, training a model on a domain with little data often leads to over-fitting. A common practical solution is to integrate data from different domains but with similar distributions and train a “general” model. Then this “general” model is deployed to serve different scenarios. The drawback of this solution is obvious, i.e., this “general” model is not the optimal for every and each target domain.

Transfer learning is a promising way of helping train a more precise model for each target domain. In this work, we deal with the task of transferring the “general” CTR model trained from the source domains to a target domain\textsuperscript{1}. In par-

\textsuperscript{1}We focus on the case of only one target domain. When there exist multiple target domains, we transfer the “general” CTR model to each target domain individually.
ticular, we focus on deep CTR models as the “general” model, pre-trained in a supervised manner on the source domains. To do so, we need to tackle the following challenges.

(C1) Existing recommendation literature is unclear on whether deep CTR models can be transferred from source domains to target domains where different domains may not share users and items. Moreover, there are various deep CTR models in the literature. Therefore, a transfer learning framework that is compatible with any deep CTR model is needed.

(C2) Deep CTR models follow an embedding & feature interaction paradigm. It is hard to determine whether and how each of these two modules are transferred to a target domain, so that the model performance on the target domain is superior.

(C3) Different training instances and features may need different amount of information from source domains as shown in Figure 1. For example, items that are less frequent in the target domain may need more information from the source domains than the more popular items in the target domain. Such fine granularity control of knowledge transfer is hardly possible to manage by experts.

Transfer learning and domain adaptation techniques are well studied in computer vision (CV) area [Yosinski et al., 2014; Rusu et al., 2016; Xuhong et al., 2018; Guo et al., 2019] and natural language processing (NLP) area [Devlin et al., 2019; Ruder et al., 2019], but not much in CTR prediction area. The typical way of performing transfer learning with deep neural networks is to fine-tune all the parameters of a pre-trained model on the source domain using data from the target domain. However, it is unclear whether fine-tuning all the parameters for all the instances in the target domain is the optimal solution. These works [Yosinski et al., 2014; Rusu et al., 2016; Xuhong et al., 2018; Guo et al., 2019] proposed in CV area suggest to import the pre-trained model information wisely. For example, ProgressiveNN (Progressive Neural Network) [Rusu et al., 2016] proposes to combine the parameters of the pre-trained network and the fine-tuned network via MLP. \( L^2 \)-SP [Xuhong et al., 2018] investigates several regularization schemes and recommends a simple \( L^2 \) penalty to encourage the similarity of the pre-trained network and the fine-tuned network. SpotTune [Guo et al., 2019] treats instances differently during fine-tuning by training a policy network to decide which layer of a model should be frozen or fine-tuned for individual instances. However, these works cannot resolve C2 and C3 if we apply them directly in CTR prediction area, since they either do not distinguish different components of a deep CTR model (such as [Guo et al., 2019]) or do not consider different network layers and individual instances (like [Xuhong et al., 2018; Rusu et al., 2016]) during the transfer learning. More importantly, these models are designed for CV where the input are continuous values that represent quantifiable values of images, which is quite different from CTR prediction area.

In this paper, we explore how transferable are parameters in a pre-trained CTR prediction model, which usually consists of an embedding layer and a feature interaction layer, from multiple source domains to a target domain. We mainly focus on transferring the parameters of a pre-trained model based on source domains with proper fine-tuning. Other transfer learning approaches such as instance based approaches [Lin et al., 2013; Zhang et al., 2014; Wang et al., 2019; Zhong et al., 2020], feature based approaches [Pan, 2010; Pan et al., 2008] and domain adaptation approaches [Ganin and Lempitsky, 2015; Long et al., 2016; Aggarwal et al., 2019; Tran et al., 2019; Liu et al., 2020] are beyond the scope of this work.

We propose an adaptive fine-tuning approach for transferring learning on deep CTR models, called AutoFT, which automatically finds a route between the pre-trained network and the siamese fine-tuning network per instance in the target domain. Exemplary routes are depicted in red color in Figure 2. In particular, to cope C1, AutoFT is a general framework to import parameters from the pre-trained model, which is compatible to various deep CTR models in the literature. Without lose of generality, we use DCN [Wang et al., 2017] model to elaborate the details of AutoFT. For C2, different transfer strategies are designed in AutoFT for different components of a deep CTR model, since different components play unique roles in CTR prediction. Specifically, we propose a field-wise transfer policy for the embedding layer and a layer-wise transfer policy for the feature interaction layers. To handle C3, we design a set of instance-based policy networks to decide which parameters should be preserved as in the pre-trained model (frozen) or fine-tuned, so that feasible parameter adaptation for different instances and features is achieved.

In summary, we make the following contributions in this paper.

- Firstly, we propose a framework AutoFT for transferring parameters of a pre-trained CTR prediction model from source domains to a target domain. AutoFT automatically finds a route between the pre-trained network and the siamese fine-tuning network per instance in the target domain and is compatible with any deep CTR models.
- We propose a field-wise transfer policy for the embedding layer, and a layer-wise transfer policy for the feature interaction layers. Feasible parameter adaption for different features and instances is achieved by designing a set of learnable policy networks.
- We compare the performance of our propose approach with many state-of-the-art methods which is also designed for re-using the parameters of pre-trained models, on two public benchmarks and one private dataset. The experimental results demonstrate the superiority of our proposed AutoFT in transfer learning.
- We also study which components or layers of a CTR model need more fine-tuning. The result shows that there is similar phenomenon to computer vision (CV) that the lower layers of the network represent more general features while higher layers need more fine-tuning to fit for a specific target domain.

2 Related Work

2.1 Deep Models in CTR prediction

Recently, deep learning based models achieve state-of-the-art performance for CTR prediction [Cheng et al., 2016; Guo et al., 2017; Qu et al., 2016; Wang et al., 2017]
Deep CTR models follow an embedding & feature interaction paradigm. Many works focus on designing new network architectures to improve the feature interaction component, aiming to better capture the nonlinear relationship among features.

Wide & Deep [Cheng et al., 2016] proposed by Cheng et al. jointly trains a wide linear model for manually designed second-order feature interactions and a deep neural network for higher-order feature interactions. DeepFM [Guo et al., 2017] and PNN [Qu et al., 2016] use an FM layer to learn second-order feature interactions and MLP to learn higher-order feature interactions. PIN [Qu et al., 2018] introduces a network-in-network architecture to model pairwise feature interactions with sub-networks rather than using simple inner product operations as in PNN and DeepFM. DIN [Zhou et al., 2018] and AFM [Xiao et al., 2017] utilize attention network to differentiate contribution of each second-order feature interactions. DCN [Wang et al., 2017] and xDeepFM [Lian et al., 2018] apply a cross operation and a compressed interaction respectively, to explicitly learn $p^{th}$ order feature interactions from $(p-1)^{th}$ order ones.

These works mainly focus on designing network architectures for the feature interaction component of deep CTR models. They achieve good performance in a single domain. In real-world applications, a well trained model in one or multiple source domains may be useful for a target domain, because sharing such information may be beneficial especially when the target domain is of limited data. In this paper, we study this problem and propose a transfer learning framework for transferring parameters of a pre-trained CTR model from source domains to a target domain which is compatible with the above mentioned deep CTR models.

### 2.2 Transfer Learning

Transfer learning and domain adaptation techniques are widely used in computer vision while they are relatively rarely explored in the CTR prediction area. For example, Yosinski et al. [Yosinski et al., 2014] experimentally quantify the generality versus specificity of neurons in each layer of a deep convolutional neural network. They report that initializing a network with transferred features from almost any number of layers can boost the generalization that lingers even after fine-tuning to the target domain. This result has yet been verified in CTR prediction area where the input feature is not usually continuous, and the model structure is quite different from computer vision.

While fine-tuning in [Yosinski et al., 2014] incorporates the prior knowledge only by initializing with a pre-trained model, ProgressiveNN [Rusu et al., 2016] retains the parameters of the pre-trained model and learns another set of parameters from the pre-trained model via fine-tuning. Then, the pre-trained parameters and fine-tuned parameters are combined via MLP, which is proven to be effective for transfer learning. $L^2$-SP [Xu et al., 2018] assumes that the pre-trained model from source domains are useful for the target model. This work explores several regularization schemes that explicitly promote the similarity between the fine-tuned model on the target domain and the pre-trained model from the source domains. They find that a simple $L^2$ regularization performs best. SpotTune [Guo et al., 2019] proposes an adaptive fine-tuning approach which aims to find the optimal fine-tuning strategy for each instance in the target domain. A policy network is learned to make routing decisions on whether to pass through the fine-tuned layers or through the pre-trained layers. More recently, PeterRec [Yuan et al., 2020] keeps the pre-trained parameters unaltered, while introduces several network layers with learnable parameters.

Our work is inspired by [Guo et al., 2019]. However, we mainly focus on exploring the parameter transferability in different components of deep CTR models which have significantly different input features and structures compared with models in computer vision. Such differences bring challenges when we transfer deep CTR models from source domains to the target domain, as stated in Section 1.

### 2.3 Cross Domain Recommendation

There are some work for cross domain recommendation that are relevant to our work. For example, CST [Pan et al., 2010], NATR [Gao et al., 2019], DARec [Yuan et al., 2019] focus on transferring feature representations, such as user/item embeddings, from source domains to target domains. Those methods are similar to model-based methods if we take the embeddings as part of the CTR model. However, these methods do not tell us whether other parts of a CTR model are transferable or not. We compare AutoFT with NATR in the experiments. Approaches such as CST and DARec that rely on the availability of rating matrix is beyond the scope of this work.

### 3 Methodology

In this section, we introduce our proposed method AutoFT, which is an automatic fine-tuning strategy that decides which layers of a deep CTR model and which input fields should be frozen or fine-tuned for each target instance. AutoFT is compatible to any deep CTR models. With the loss of generality and for the ease of presentation, we select a representative CTR model, i.e., Deep & Cross Network (DCN) [Wang et al., 2017] as the backbone model for our fine-tuning method AutoFT. For clarity, we start by introducing the backbone DCN model in Section 3.1. Then, the details of the proposed AutoFT framework are presented in Section 3.2. Finally, in Section 3.3, we elaborate learning the policy network in AutoFT by using the Gumbel Softmax trick.

#### 3.1 Backbone DCN Model

As stated earlier, most deep CTR models follow an embedding & feature interaction paradigm, which consists of embedding layer, feature interaction layers and prediction layer. DCN, introduced by Wang et al. [Wang et al., 2017], also an instantiation of this paradigm. We present the details of DCN model in this section.

**Embedding layer.** In CTR prediction, one-hot or multi-hot encoding is used to represent an input instance, as in Eq.(1), which includes multiple categorical fields, such as item category.

$$\mathbf{x}_{\text{hot}} = [x_{\text{hot},1}, x_{\text{hot},2}, \cdots, x_{\text{hot},m}],$$ (1)

where $m$ is the number of fields and $x_{\text{hot},i}$ is the one-hot or multi-hot encoding vector of the $i$-th field in this instance.
Each field consists of possibly many feature values, therefore the one-hot encoding vector $x_{\text{hot}}$ is a high-dimensional sparse binary vector. To reduce the dimensionality, the embedding layer transforms the binary one-hot vectors into dense low-dimensional vectors, as in Eq. (2).

$$x_i = V_i x_{\text{hot},i}, \quad (2)$$

where $x_i$ is the embedding vector of $x_{\text{hot},i}$, $V_i \in \mathbb{R}^{k \times n_i}$ is the corresponding embedding matrix of the $i$-th field, and $k, n_i$ are the embedding size and number of features in the $i$-th field. The embedding matrices of all the fields are optimized together with network parameters.

For a multivariate field, the representation of the multi-hot vector $x_{\text{hot},i}$ with $k$ elements $x_i[j] = 1$ ($j = i_1, i_2, \cdots, i_k$) is the average of the individual embeddings:

$$x_i = \frac{1}{k} \sum_{j=1}^{i_k} V_j x_{\text{hot},i}[j]. \quad (3)$$

The final output of the embedding layer is the concatenation of embedding vectors of all the fields:

$$x = [x_1, x_2, \cdots, x_m]. \quad (4)$$

**Feature Interaction layers.** The key challenge of CTR prediction is to model feature interactions effectively. In DCN model, the feature interaction layers consist of a cross network and a deep network.

The cross network applies explicit feature interactions in an efficient way. It consists of multiple layers, where each layer produces higher-order interactions based on existing ones, and keeps the interactions from previous layers. Let $x^{(l)}$ denote the $l$-th cross layer. The output cross layer $x^{(l+1)}$ is generated as in Eq. (5).

$$x^{(l+1)} = x^{(l)} x^{(l)} W_c^{(l)} + b_c^{(l)} + x^{(l)}, \quad (5)$$

where $w_c^{(l)}$ and $b_c^{(l)}$ are the weight and bias terms of the $l$-th cross layer, and $x^{(0)}$ is first layer of cross network (which is equivalent to the output of embedding layer).

The deep network, in parallel with the cross network, is a fully-connected neural network, introduced to capture high-order nonlinear feature interactions. Let $h^{(l)}$ denote the $l$-th deep layer, the output deep layer $h^{(l+1)}$ is shown in Eq. (6).

$$h^{(l+1)} = \text{ReLU}(w_d^{(l)} h^{(l)} + b_d^{(l)}), \quad (6)$$

where $w_d^{(l)}$ and $b_d^{(l)}$ are weight and bias terms for the $l$-th deep layer. ReLU is an activation function.

**Prediction layer.** The prediction layer combines the outputs from the cross network and the deep network, i.e., $x^{(L_c)}$ and $h^{(L_d)}$ to make prediction, where $L_c$ and $L_d$ represent the number of layers in the cross network and the deep network. More specifically, the prediction is based on the concatenation of the two output vectors as in Eq. (7).

$$\hat{y} = \text{Sigmoid}(w_o [x^{(L_c)}, h^{(L_d)}] + b_o), \quad (7)$$

where $w_o, b_o$ are the weight and bias terms for the prediction layer. Sigmoid is an activation function.

The loss function is cross-entropy of the predicted values $\hat{y}$ and the labels $y$ with a regularization term,

$$L(y, \hat{y}) = -y \log(\hat{y}) - (1 - y) \log(1 - \hat{y}) + \lambda \Vert W \Vert^2, \quad (8)$$

where $W$ represents the set of parameters of DCN model, and $\lambda$ is a hyper-parameter to balance the prediction error and the regularization term.

### 3.2 AutoFT Framework

The key idea of AutoFT is to train a set of learnable policy networks, one of which is to decide which fields of the input instance should be frozen or fine-tuned (referred as field-wise transfer policy), while the others make routing decisions.
on whether to pass the input through the pre-trained network layers or the siamese fine-tuning network layers (referred as layer-wise transfer policy). Following the definition of transfer learning [Cao et al., 2010], the source domains are defined as $S$ and the target domain is represented as $T$. The key notations of the pre-trained and fine-tuned networks are shown in Table 1.

Table 1: Related notations of the pre-trained and fine-tune model.

| Notation | Meaning |
|----------|---------|
| $V^S$    | pre-trained embedding matrix in source domain |
| $V^T$    | fine-tuned embedding matrix in target domain |
| $x^s$    | embedding vector of a source instance |
| $x^T$    | embedding vector of a target instance |
| $w^S_l$, $b^S_l$ | pre-trained weight and bias terms of the cross network in source domain |
| $w^T_l$, $b^T_l$ | fine-tuned weight and bias terms of the cross network in target domain |
| $x^{(l)}_S$ | $l$-th cross layer of DCN model in source domain |
| $x^{(l)}_T$ | $l$-th cross layer of DCN model in target domain |
| $w^S_l$, $b^S_l$ | pre-trained weight and bias terms of the deep network in source domain |
| $w^T_l$, $b^T_l$ | fine-tuned weight and bias terms of the deep network in target domain |
| $h^{(l)}_S$ | $l$-th deep layer of DCN model in source domain |
| $h^{(l)}_T$ | $l$-th deep layer of DCN model in target domain |
| $\mathbb{W}^S$ | parameters of pre-trained DCN neural network in source domain |
| $\mathbb{W}^T$ | parameters of fine-tuned DCN neural network in target domain |

Field-wise transfer policy. For the embedding layer, the policy network takes the pre-trained embedding $x^S$ from source domains as input and outputs a binary vector $p_c(x^S)$. The $i$-th value in this vector, denoted as $P^i_c(x^S)$ in Eq.(10), decides whether the $i$-th field of features should use pre-trained embedding parameters $V^S$ or the fine-tuned embedding parameters $V^T$. $x^T_i$ represents feature embeddings where each field is selected either from pre-trained parameters or from fine-tuned parameters, controlled by the policy network.

$$x^T_i = P^i_c(x^S)V^T_{i,\text{hot},i} + (1 - P^i_c(x^S))V^T_{i,\text{not},i}. \quad (10)$$

Noted that $V^T$ and $V^T$ are different embedding matrices. $V^T$ is the embedding matrix in Fine-Tune model while $V^T$ is the embedding matrix in AutoFT as shown in Figure 2.

Layer-wise transfer policy. For the cross network and deep network, the input of the policy network is $x^T$ computed based on Eq.(10). The outputs are two binary vectors $P^c_c(x^T)$ and $P^d_d(x^T)$, to decide a "route" from the embedding layer to the prediction layer in deep network and cross network, respectively. Each binary value in each of two vectors determines the direction of each step in the route, by specifying whether the parameters of the current layer should inherit from the pre-trained model or from the fine-tuned model, as shown in Figure 2.

Specifically, in the cross network, the output of $l$-th cross layer is generated as in Eq.(11).

$$x^{(l+1)T} = P^c_c(x^T)F_c(x^{(l)T}) + (1 - P^c_c(x^T))\hat{F}_c(x^{(l)T}). \quad (11)$$

$F_c(\cdot)$ is a cross layer formulated in Eq.(5), which take $x^{(l)}$ as input and outputs $x^{(l+1)}$ with frozen pre-trained parameters $w^S_l$ and $b^S_l$. Similarly, $\hat{F}_c(\cdot)$ is a cross layer with the fine-tuned parameters $\hat{w}^T_l$ and $\hat{b}^T_l$.

In the deep network, the output of the $l$-th deep layer $h^{(l+1)T}$ is generated as in Eq.(12).

$$h^{(l+1)T} = P^d_d(x^T)F_d(h^{(l)T}) + (1 - P^d_d(x^T))\hat{F}_d(h^{(l)T}). \quad (12)$$

$F_d(\cdot)$ is a deep layer defined in Eq.(6) with frozen pre-trained parameters $w^S_l$ and $b^S_l$. Similarly, $\hat{F}_d(\cdot)$ is a deep layer with the fine-tuned parameters $\hat{w}^T_l$ and $\hat{b}^T_l$.

The prediction layer combines the outputs of the cross network and the deep network to predict the click probability. It has been proven by [Yosinski et al., 2014] that the prediction learns features that are specific to a particular task. Thus, we always fine-tune the parameters of the prediction layer.

The loss function is the same as the one in Eq.(8). During the training phase, the parameters from the pre-trained model are frozen, while other parameters are trainable. During the inference phase, the policy networks generate a route from the embedding layer to the prediction layer, where each step of the route passes by either the pre-trained model or the fine-tuned model. Since the policy networks are lightweight networks, the inference time of AutoFT is almost the same as DCN.
3.3 Gumbel-Softmax Trick

AutoFT makes binary decisions at the embedding layer, the feature interaction layers (i.e., the cross network and deep network), to choose to inherit parameters from the pre-trained model or from the fine-tuned model. Such binary decisions are made by policy networks. The output of the policy networks are discrete values which make the parameters in the policy networks non-differentiable. Therefore, it is difficult to optimize the network with back propagation. The Gumbel-Softmax trick [Jang et al., 2016] is an approach to circumvent this problem. This trick provides a simple and effective way to draw samples from a categorical distribution parameterized by \( \{ \alpha_0, \alpha_2, \cdots, \alpha_{z-1} \} \), where \( \alpha_i \) is the probability of category \( i \), and \( z \) is the number of categories. In this paper, there are two categories, \( \alpha_0 \) and \( \alpha_1 \), which are probabilities of using the frozen pre-trained parameters or the fine-tuned parameters.

During the forward pass, \( z \) samples \( G_0, \cdots, G_{z-1} \) are sampled from a standard Gumbel distribution \( G = -\log(-\log(u)) \), where \( u \) is sampled from a uniform distribution, i.e., \( u \sim U[0,1] \). Then each element in a policy vector \( p \) (corresponding to Eq.(9)) is computed by Eq.(13), where \( \alpha_i \) is the output of the fully-connected layers in the policy networks.

\[
p_i = \arg \max_i [\log \alpha_i + G_i] \quad \text{for } i = 0, \cdots, z - 1 \quad (13)
\]

The argmax in Eq.(13) is non-differentiable. Thus, during the backward pass, we replace the non-differentiable sample from a categorical distribution with a differentiable sample from a novel Gumbel-Softmax distribution which can be smoothly annealed into a categorical distribution. The gradient of the discrete samples are approximated by computing the gradient of the continuous softmax relaxation as in Eq.(14).

\[
Y_i = \frac{\exp((\log \alpha_i + G_i)/\tau)}{\sum_{j=1}^{z} \exp((\log \alpha_j + G_j)/\tau)} \quad \text{for } i = 0, \cdots, z - 1 \quad (14)
\]

where \( \tau \) is a temperature parameter, which controls the discreteness of the output vector \( Y \). When \( \tau \) becomes closer to 0, the samples from the Gumbel-Softmax distribution become indistinguishable from the discrete distribution. The Gumbel-Softmax distribution is smooth for \( \tau > 0 \) and therefore has well-defined gradients with respect to the parameters \( \alpha_i \).

By using a standard classification loss for the target domain, the policy network is jointly trained with the fine-tuned parameters to find the optimal fine-tune strategy that maximizes the accuracy of CTR prediction in the target domain. This whole process is illustrated in Figure 2.

4 Experiments

In order to verify the effectiveness of the proposed framework AutoFT, we conduct extensive experiments on two public benchmark datasets and one industrial dataset. We mainly focus on the following research questions (RQs).

- **RQ1**: Is AutoFT able to positively transfer the pre-trained model to the target domain, can it outperform state-of-the-art approaches?

- **RQ2**: How do different components of proposed AutoFT, i.e., field-wise transfer policy and layer-wise transfer policy, contribute to the performance?

- **RQ3**: Is the policy based learning framework AutoFT compatible with any deep CTR models, such as DNN and DeepFM?

- **RQ4**: Which layers of the deep CTR models need more fine-tuning?

4.1 Datasets

Experiments are conducted on the following two public datasets (MovieLens-1M and Amazon review data) and one private industrial dataset. The statistics of the datasets are in Table 2.

| Datasets        | MovieLens | Amazon | Industrial data |
|-----------------|-----------|--------|-----------------|
| Source training | 602,975   | 6,600,984 | 68,129,281 |
| Target training | 197,025   | 2,052,279 | 4,296,836  |
| Source validation | 75,253 | 8,201,231 | 9,294,471  |
| Target validation | 24,737 | 513,069 | 622,236    |
| Source testing  | 75,531    | 8,201,231 | 9,259,634  |
| Target testing  | 24,678    | 513,069 | 632,947     |
| Ratio of positive | 0.3753 | 0.6040 | 0.0232       |
| Users’ overlap rate | 0.0% | 0.3% | 1.7%       |
| Items’ overlap rate | 100.0% | 0.0% | 78.6%       |

**MovieLens-1M dataset**: This dataset includes 1 million movie rating records over thousands of movies and users [Harper and Konstan, 2015]. The features we used are user id, genre, occupation, user behavior, movie id, release year, and movie genres. The ratings greater than 3 are taken as positive samples, and others are taken as negative samples [Volkovs and Yu, 2015]. The dataset is randomly divided into the training, validation, and test sets with a ratio of 8:1:1. As we analysed in the data, the female and male users have different preferences and click behaviours about movies. Thus, we regard male as the source domain and female as the target domain.

**Amazon review data**: This dataset contains product reviews and metadata from Amazon, including 24 categories spanning from 1996 to 2018 [Ni et al., 2019]. The data we used are 5-cores records of products in Toys and Games and Video Games. Each of the users and items have 5 reviews, respectively. Different from Movielens-1M dataset, we take ratings greater than 4 as positive samples to balance the positive samples and negative samples. The features we used are reviewerID,asin,vote,style and reviewTime. The training, validation, and test sets are also divided randomly with a ratio of 8:1:1. Records of Toys and Games are used as source domain since this category has more records than Video Games, which is more reasonable to transfer general knowledge.

**Industrial dataset**: This dataset is collected from a real commercial recommender system deployed in the company

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3 https://www.grouplens.org/datasets/movielens/

4 https://www.nijianmo.github.io/amazon/index.html
X’s App Store. The dataset contains app features (e.g., ID, category), user features (e.g., user’s click behavior history) and context features (e.g., time). We choose the two recommendation scenarios, Must-have Apps and Novel-Fun as the source domain and target domain, respectively. Each domain contains tens of thousands of apps and more than ten million users. We collect 73M records from the download logs, which represent the operations of users to apps. In training process, the source domain records is used to training the model with the target domain data be the validation and test dataset to evaluate the model.

4.2 Baselines & experimental settings

We compare AutoFT with multiple baseline methods to verify its effectiveness for CTR prediction. All these methods are evaluated on the testing data from the target domain.

We firstly introduce three straightforward baseline methods that are easy to think of without transferring any parameters from the pre-trained model. Target-only, Source, and All, which use Source-only, and All domains for training, respectively.

- **Target-only** is the method to use target domain data for both training and testing.
- **Source-only** is to use source domain data for training and use target domain data for testing.
- **All** is to use both source and target domain data for training and use target domain data for testing.

Then we describe four representative state-of-the-art baseline approaches, i.e., Fine-tune, ProgressiveNN, $L^2$-SP and SpotTune, of transferring parameters from the pre-trained model. The pre-trained model is learned either from Source-only or All method.

- **Fine-Tune** [Yosinski et al., 2014] is the method to learn a model which is initialized by a pre-trained model. Then all the parameters of the model are fine-tuned using data from the target domain.
- **PTU** [Zhang et al., 2019] is a parameter transfer unit, that produces a weighted sum of the activations from both the already trained source domain network and the target domain network.
- **ProgressiveNN** [Rusu et al., 2016] proposes to aggregate the pre-trained parameters to the fine-tuning parameters with an element-wise non-linear function. The next layer receives input from both previous pre-trained and fine-tuning layers via lateral connections.
- **$L^2$-SP** [Xuhong et al., 2018] is a regularization-based method for fine-tuning. A simple $L^2$-penalty between the shared pre-trained network parameters $W^S$ and the fine-tuning parameters $W^T$ is applied to constrain the effective search space around the initial pre-trained model.
- **SpotTune** [Guo et al., 2019] aims to dynamically route blocks in Residual Network model, which improves the classification performance in CV. For the CTR prediction tasks, this method is corresponding to our layer-wise policy network which is only used to control the choice in the cross and deep network.

- **NATR** [Gao et al., 2019] resolves the key challenges in leveraging transferred item embeddings. The two level attention design allows NATR to distill useful signal from transferred item embeddings, and appropriately combine them with the data of the target domain.

All methods are implemented with TensorFlow$^4$ and trained on GPUs (Tesla P100) with Adam optimizer [Kingma and Ba, 2015]. All experiments are repeated five times and the average values are reported. For the hyper-parameters, we tune learning rate to be from 0.001 to 0.0001, set batch size to be 8000 and embedding dimension to be 80. Note that, DCN are used for backbone network in AutoFT. For network architecture, the cross network has 3 layers iteration, the deep network has 4 layers with dimensions specifically of 1024, 512, 256, 128. Finally, the common evaluation metrics, AUC (Area Under ROC) and Logloss (cross-entropy), are used for comparison.

4.3 Overall Performance (RQ1)

The performance of the baseline approaches and our proposed framework AutoFT is shown in Table 3. We divide the results into three groups. The first group shows the results of the basic baseline method Target-only. The second group of methods are based on a pre-trained model, i.e., Source-only, that is trained on data from source domains. The third group of methods are based on a pre-trained model, i.e., All, that is trained on data from all domains. The best results of the baseline methods in the second and third groups are underlined. From this table, we have the following observations.

**Firstly**, AutoFT performs best with respect to AUC among all the approaches on all datasets no matter that the pre-trained model is based on Source-only or based on All, which demonstrates the effectiveness of our proposed framework. Moreover, the state-of-the-art baseline approaches such as ProgressiveNN, PYU, $L^2$-SP, and SpotTune, though do not dominate each other, generally performs better than the basic baseline approaches such as Target-only, Source-only, and All. However, their performance is inferior to AutoFT since they do not distinguish different component of a CTR model, thus, are less flexible when transferring different amount of valuable information for different components or instances.

**Secondly**, we can observe that the approaches that include both source domains and target domain data perform better than Target-only and perform much better than Source-only. This observation implies that importing extra data to the target domain can positively transfer information to improve the prediction accuracy. For the scenario that share more common items, such as MovieLens-1M and Industrial data, the benefit of transferring is higher than that share less common items, such as Amazon Review.

**Thirdly**, we found that approaches using All as the pre-trained model generally performs better than approaches using Source-only as the pre-trained model. This is probably for the reason that All include more “general” features and parameters than Source-only, which indicates that a more “general” model that includes information from multiple domains

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$^4$https://www.tensorflow.org/
Table 3: Performance comparison of different methods. * denotes statistically significant improvement (measured by t-test with p-value < 0.005) over baselines.

| Method           | MovieLens-1M AUC | Amazon review data AUC | Industrial dataset AUC |
|------------------|------------------|------------------------|------------------------|
|                  | LogLoss          | LogLoss                | LogLoss                |
| Target-only      | 0.7561 0.6791    | 0.7120 0.6461          | 0.8949 0.03948         |
| Source-only      | 0.7112 0.6701    | 0.6010 0.6549          | 0.8084 0.04723         |
| Source-Fine-Tune | 0.7807 0.5609    | 0.7128 0.6007          | 0.9010 0.03907         |
| Source-ProgressiveNN | 0.7817 0.5445 | 0.7124 0.6023          | 0.9019 0.03884         |
| Source-PTU       | 0.7809 0.5552    | 0.7130 0.5999          | 0.9013 0.03904         |
| Source-$L^2$-SP  | 0.7813 0.5508    | 0.7131 0.5999          | 0.9011 0.03905         |
| Source-SpotTune  | 0.7814 0.5506    | 0.7133 0.5997          | 0.9016 0.03885         |
| Source-NATR      | / /             | / /                    | 0.9014 0.03904         |
| Source-AutoFT    | 0.7822 0.5504*   | 0.7138* 0.5968*        | 0.9024* 0.03882*       |
| All              | 0.7776 0.6137    | 0.7106 0.6042          | 0.9039 0.03857         |
| All-Fine-Tune    | 0.7843 0.5430    | 0.7141 0.6004          | 0.9040 0.03855         |
| All-ProgressiveNN| 0.7832 0.5437    | 0.7146 0.5965          | 0.9040 0.03852         |
| All-PTU          | 0.7863 0.5415    | 0.7152 0.5976          | 0.9039 0.03858         |
| All-$L^2$-SP     | 0.7864 0.5407    | 0.7143 0.6002          | 0.9046 0.03847         |
| All-SpotTune     | 0.7885 0.5398    | 0.7146 0.5980          | 0.9044 0.03878         |
| All-NATR         | / /             | / /                    | 0.9048 0.03846         |
| All-AutoFT       | 0.7932 0.5375*   | 0.7166* 0.5945*        | 0.9052* 0.03843*       |

that are relevant to the target domain can boost the performance of the target domain to a larger margin.

4.4 Ablation study (RQ2)

In this section, we study how field-wise transfer policy and layer-wise transfer policy, which are corresponding to different policy networks in AutoFT, contribute to the performance. In the experiments, we only keep the policy network for the embedding layer and remove other policy networks from All-AutoFT. This method is denoted as Embedding in Table 4. Similarly, Cross, Deep, Cross & Deep represent the methods that only keep the policy networks for the cross layers, the deep layers and both the cross layers and deep layers, respectively.

From Table 4, we can observe that the performance of all variants drops when we remove certain policy networks from AutoFT which verifies that both field-wise transfer policy and layer-wise transfer policy play important roles in the performance. For MovieLens-1M data, the drop of the performance with respect to AUC of Cross and Deep is significant compared with AutoFT when we remove field-wise policy network and one of the layer-wise policy networks. For Amazon data, the drop of their performance is less significant. That implies for the dataset that shares more items in the source and target domains, the pre-trained model contains more general information that help the prediction in the target domain, which should be included by policy networks.

4.5 Compatibility of AutoFT (RQ3)

In this section, we conduct experiments to verify whether AutoFT is compatible with different deep CTR models. We choose three representative CTR prediction models for our experiment, they are DCN, DNN and DeepFM. We keep the network architectures of deep layers of DCN and DNN to be the same which are of size 1024, 512, 256, 128. We set the deep layers of DeepFM to be of size 400, 400, 400 to check if our proposed framework works for a different network size. The pre-trained model is the baseline All. The experimental results are shown in Table 5. The difference between All-Fine-Tune and All-AutoFT is that All-Fine-Tune does not include any transfer policies, all its parameters are fine-tuned. From Table 5, we can observe that for various deep CTR models, AutoFT always achieves better results than the Fine-Tune method, which demonstrates the compatibility of our proposed framework.

Table 4: The performance of policy net of each component in DCN.

| Policy-based Component | MovieLens-1M AUC | MovieLens-1M LogLoss | Amazon review AUC | Amazon review LogLoss |
|-----------------------|------------------|----------------------|-------------------|-----------------------|
| All-Fine-Tune         | 0.7843 0.5430    | 0.7141 0.6004        | 0.7141 0.6004     |
| Embedding             | 0.7878 0.5404    | 0.7135 0.5995        | 0.8011 0.03855    |
| Cross                 | 0.7866 0.5412    | 0.7136 0.5990        | 0.8047 0.03855    |
| Deep                  | 0.7854 0.5432    | 0.7152 0.5968        | 0.8047 0.03847    |
| Cross & Deep          | 0.7885 0.5398    | 0.7146 0.5980        | 0.8047 0.03878    |
| All-AutoFT            | 0.7932 0.5375*   | 0.7166* 0.5945*      | 0.9052* 0.03843*  |

Table 5: Compatibility of AutoFT with classic deep CTR models.

| Model               | MovieLens-1M AUC | MovieLens-1M LogLoss | Amazon review AUC | Amazon review LogLoss |
|---------------------|------------------|----------------------|-------------------|-----------------------|
| DCN Fine-Tune       | 0.7843 0.5430    | 0.7141 0.6004        | 0.7141 0.6004     |
| DCN AutoFT          | 0.7932 0.5375    | 0.7166 0.5945        | 0.7166 0.5945     |
| DNN Fine-Tune       | 0.7754 0.6198    | 0.7131 0.6002        | 0.7131 0.6002     |
| DNN AutoFT          | 0.7840 0.5453    | 0.7145 0.5987        | 0.7145 0.5987     |
| DeepFM Fine-Tune    | 0.7780 0.5844    | 0.7120 0.5997        | 0.7120 0.5997     |
| DeepFM AutoFT       | 0.7852 0.5434    | 0.7128 0.5991        | 0.7128 0.5991     |
Figure 3: Visualization of AutoFT. The first row is about deep layers, and the second row is about the cross layers.

4.6 Visualization of Policy (RQ4)

To better understand the fine-tuning decisions learned by the policy networks, we visualize them on the two public benchmark datasets. For field-wise transfer policy, we count the number of instances that either use the pre-trained embedding or the fine-tuned embedding. However, we do not find any special trend among different fields. For layer-wise transfer policy, we counted each instance’s layer-wise decision of using pre-trained or fine-tune parameters during testing. The percentage of the pre-trained and fine-tune policy in each layer based on MovieLens-1M and Amazon data are shown in Figure 3. For example, a light-blue pre-train bar with a number of 0.2 means 20% of the instances in the test target domain share the pre-trained parameters in this layer and the 80% of instances use the fine-tuned parameters. The visualization shows that different datasets and different layers have specific fine-tuning policies, which validates our hypothesis that it is more accurate to have an instance-based fine-tuning policy for CTR prediction. AutoFT allows us to automatically learn the right policy for each dataset, as well as for each training instance, without much manual effort. By observing the percentages of pre-train and fine-tune bars in each sub-figures, we find that more and more instances choose the fine-tune direction on higher layers. This also verifies that the lower layers could learn more general features and the parameters in higher layers are more specific to each domains, which need to be fine-tuned during transfer learning.

5 Conclusion

In this paper, we propose a framework AutoFT to automatically incorporate parameters from a pre-trained model to facilitate the CTR prediction accuracy in a new target domain. The field-wise policy in AutoFT decides which fields of embedding features should be inherited from the pre-trained model or should be fine-tuned. The layer-wise policy generates route decisions between pre-trained and fine-tuned parameters for each layer in the deep and cross networks. To achieve this, lightweight policy networks are jointly trained with the target domain using a Gumbel-Softmax trick. The proposed framework is generally applicable to many deep CTR models. Extensive offline experiments demonstrate the superior performance of AutoFT.

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