Learning to Recommend via Meta Parameter Partition

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Abstract
In this paper we propose to solve an important problem in recommendation - user cold start, based on meta leaning method. Previous meta learning approaches finetune all parameters for each new user, which is both computing and storage expensive. In contrast, we divide model parameters into fixed and adaptive parts and develop a two-stage meta learning algorithm to learn them separately. The fixed part, capturing user invariant features, is shared by all users and is learned during offline meta learning stage. The adaptive part, capturing user specific features, is learned during online meta learning stage. By decoupling user invariant parameters from user dependent parameters, the proposed approach is more efficient and storage cheaper than previous methods. It also has potential to deal with catastrophic forgetting while continually adapting for streaming coming users. Experiments on production data demonstrates that the proposed method converges faster and to a better performance than baseline methods. Meta-training without online meta model finetuning increases the AUC from 72.24% to 74.72% (2.48% absolute improvement). Online meta training achieves a further gain of 2.46% absolute improvement comparing with offline meta training.

1 Introduction

Personalized recommender systems are playing more and more important roles in web-based and mobile applications. The goal of learning to recommend is to learn a training paradigm that takes as input a set of items from a user’s history and generates a function or user model that can be applied to new items and to predict how likely this user will click that item – click through rate (CTR) prediction. One of the key challenges faced by conventional Matrix Factorization [19, 16] methods is to make personalized recommendation for new users arriving sequentially – user cold start problem.

A common way to solve cold start problem is by leveraging information from other users to help with model training. For example, McMahan et al. [22] propose Federated learning by using a unified model for all users which is joint trained with all user data. The limitation with such approach is that the learned model is biased toward major interests and may not reflect personal interests of new users due to lacking training data for them. Meta learning algorithms such as MAML [9] provide a promising way to learn a good initialization for new task/user models. However, previous meta learning approaches [6] finetune all parameters for each new user, which is both computing and storage expensive.

In this paper, we propose to divide model parameters into fixed and adaptive parts, and we develop a two-stage meta learning algorithm to learn them separately. The fixed part, capturing user invariant features, is shared by all users and is learned during offline meta learning stage. The adaptive part, capturing user specific features, is learned during online meta learning stage. By decoupling user invariant parameters from user dependent parameters, the proposed approach is more efficient and storage cheaper than previous methods. It also has potential to deal with catastrophic forgetting while continually adapting for streaming coming users.

We evaluated the proposed algorithm on the real-world problem of news feed recommendation. The production dataset was collected from our news recommender platform. We trained the model with around 595k records from 57k users and evaluated on 17k records from 2k new users. Each training and test users have only 10 and 8 records per session in average, respectively. This is a
typical few-shot learning setting. The experimental results demonstrate that the proposed method converges faster and to a better performance than baseline methods. Meta-training without online meta model finetuning increases the AUC from 72.24% to 74.72% (2.48% absolute improvement). Our algorithm continuous to improve with additional training examples/ iterations during online meta training and achieves a further gain of 2.46% absolute improvement over offline meta training.

Our main technical contributions include three aspects: First, we divide model parameters into fixed and adaptive parts for capturing user invariant and user dependent features separately. Second, we developed an offline and an online meta learning algorithms to learn fixed and adaptive parameters, respectively. Third, we evaluated our algorithm on production data and demonstrates its advantages over conventional methods.

2 Related Work

Our work is closely related to CTR prediction, few-shot learning, meta learning, online learning and continual learning. In this section, we provide a brief summary of related work in these areas.

CTR prediction: In recently years, several deep learning- based approaches [20, 32, 31, 25, 8, 11] have been applied to CTR prediction in recommendation systems. Deep neural network (DNN) has potential to learn expressive features for accurate CTR prediction. CNN- based models [20] are biased to the interaction between neighboring features. RNN-based models [32] are suitable for data with sequential dependency. FNN-based model [31] is limited by the capacity of the pretrained factorization machine (FM). PNN [25] introduces product-layer between embedding and fully-connected layers. Wide-Deep [8] combines wide and deep models where wide-part relies on feature engineering. DeepFM [11] models both low and high order feature interaction in an end-to-end manner. More recently reinforcement learning based methods [34, 35, 36, 7] have been proposed for modeling user behavior and item recommendation. All these methods do not handle cold-start problem very well. In contrast, our approach can handle users with fewer records very well by using online meta learning.

Few-shot learning: The tremendous gains in DNN relies on large amount of labeled training data. However, in many situations such as cold-start problem in recommendation system, the labeled training data for new users are very limited. This requires to solve the problem with few-shot learning [17] techniques. One popular way to deal with limited training data is transfer learning [24] which pretrains the model on a source task with large amounts of data and finetunes on a target task with small amounts of data. An extension of transfer learning is multi-task learning [4] when a set of source tasks is available for pretraining the model. In contrast to these few-shot learning methods, we employ meta learning for transferring knowledge shared among users. As shown in Figure 1, meta learning generates a better model parameter initialization than both transfer learning and multi-task learning.

Meta learning for recommendation: Meta learning [27, 9, 23] provides an effective way to perform transfer learning across users by means of shared parameters [30], shared model [6], or by shared initialization [6]. All these methods assume that the training data are available at once and train the model in batch mode. In contrast, our approach works in a more realistic scenario where training data arrives in a sequence. Recently, [10] proposes an online meta learning algorithm for processing sequential data and show benefits on several computer vision tasks. A drawback with these meta learning approaches is that they finetune all parameters for each new user, which is both computing and storage expensive. In contrast, our approach enables all user models share user-invariant parameters which saves both storage and time for adapting.

Continual learning: Our problem setting is related to continual learning [29, 33]. Continual learning with neural network has been explored in recent years. Based on the way for overcoming catastrophic forgetting, current methods can be classified into approaches with fixed model size and with increasing model size. Approaches with fixed model size either employ certain constraints [15, 3] to control parameter changes when learning new concepts/tasks or use additional memory [21, 26, 1, 2] to store certain information about previous data/tasks for retraining purpose. Approaches with increasing model size [18] learn new tasks with added small amount of parameters while keeping the
previously learned parameters fixed. Unlike previous work, our approach decouples user invariant parameters from user dependent parameters and has potential to deal with catastrophic forgetting by keeping user invariant parameters fixed and only updating user dependent parameters.

**Online learning:** Similar to the setting of continual learning, online learning handles a sequential setting with streaming tasks. One early work is Follow the Leader (FTL) [12] followed with various improvements [5, 13, 28]. We cast meta learning in an online learning setting and derived an efficient online meta learning algorithm that captured the practice of online learning and leads to promising experimental results.

### 3 Problem Formulation

A common way of building personalized recommender systems is to estimate the click through rate (CTR) of a user – the probability that the user will click on a recommended item, and use the CTR to rank the items for displaying to the user. Therefore, accurate CTR prediction is important for recommender systems.

#### 3.1 Personalized CTR Prediction Problem

We formulate CTR prediction as a binary classification problem. The training data is a set of $n$ instances $(X, y)$, where $X$ is an m-field (or m-slot) data record usually consisting of a pair of user and item attributes, and $y$ indicates whether the user click the item or not. $y = 1$ means that the user click the item, and $y = 0$ otherwise. The problem is to learn a function or user model parameterized with $\theta$ for predicting the probability of a user clicking a specific item:

$$\hat{y} = f_{CTR}(x; \theta),$$

where $x = [x_{slot_1}, ..., x_{slot_m}]$.

Conventional recommendation system uses a single unified user model for predicting a new user’s CTR and the model is trained with all user data. In contrast, personalized recommendation system has a model for each user, which is trained with each user’s own data. When the training data is few for a new or occasional user, the learned model will be overfitting to the training data. Meta learning provides a way to handle few-shot learning as shown below.

#### 3.2 Meta Learning for Model Initialization

We consider learning a user model for predicting the user CTR as a task and cast personalized CTR prediction in a meta learning setting. The underlying idea of meta learning is to use a set of source tasks $\{\tau^1, ..., \tau^k\}$ to learn a meta model whose parameters is used to initialize the parameters of
4 Two-Stage Meta Learning Algorithm

Our approach contains a meta model and a user model for each user. The meta model is used to initialize the user model with $\theta^0$ and the user model provides meta-gradient $\nabla\theta_0$ for updating the meta model (see Figure 2). Our training consists of two stages: offline meta training on the source tasks and online meta training and test on the target tasks. During offline learning stage, the meta model is trained to capture user invariant features and to provide a good initialization for each user model. During online learning stage, each user model is trained for adapting personal features to changing data distribution while keeping user invariant features captured by meta model fixed. By decoupling user invariant parameters from user dependent parameters, the proposed approach not only saves storage and time for adapting, but also can deal with catastrophic forgetting while continually adapting to user specific parameters. The following subsections describe the two stages in detail.

4.1 Offline Meta Learning An Initialization

The goal of offline meta learning is to train the meta model for capturing user invariant features and to provide a good initialization for each user model. Let $\theta^0$ be the parameters of meta model and
θ^t (t ∈ [1, n]) be the parameters of task/user τ_t. Algorithm 1 summarizes the offline meta learning procedure which is adopted from Reptile [23] – a simplified MAML.

**Algorithm 1 Offline Meta Learning Algorithm**

**Input:** Innerloop steps N, meta loop steps M

Initialize \( \theta^0 \)

for \( \text{step} = 1 \) to \( M \) do

Sample \( n \) tasks from source tasks

for each new task \( \tau_t \) do

Initialize \( \theta^t \) with \( \theta^0 \)

\( \theta^t \leftarrow \text{SGD}(\theta^t; D^t_{\text{train}}, \alpha) \)

end for

\( \theta^0 \leftarrow \theta^0 - \beta(\theta^0 - \theta^t) \)

end for

The offline meta learning procedure consists of two loops. The outer loop updates the meta model parameters and the inner loop updates the training task parameters. In the beginning of the algorithm, the meta model is initialized with random noise. In each inner loop, a task is sampled from source task set and the task model parameters are initialized with meta model parameters. Then \( k \) batches of data are sampled from the task for updating the task model parameters with \( k \) SGD steps. In each outer loop, the meta model is updated based on meta-gradient calculated with Eq.(2).

### 4.2 Online Meta Learning for Personalized Finetuning

In online setting, both users and user click records arrive sequentially. We derive an online meta learning algorithm to update each user’s model incrementally as training data available once the user either click or skip the recommended item. Here we use the meta model learned in the offline training stage to initialize each user model and fine-tune the embedding and classifier layers while keeping the rest layers fixed. Therefore, we split the model parameters into two groups: a fixed one and an adaptive one as follows \( \theta = [\theta_{\text{fixed}}, \theta_{\text{adaptive}}] \). Algorithm 2 summarizes the online meta learning algorithm.

**Algorithm 2 Online Meta Learning Algorithm**

**Input:** Innerloop steps N, meta loop steps M

Initialize \( \theta^0 = [\theta^0_{\text{fixed}}, \theta^0_{\text{adaptive}}] \) with meta parameters learned in the offline stage

for \( \text{step} = 1 \) to \( M \) do

for each new task \( \tau_t \) arriving sequentially from target tasks do

Initialize \( \theta^t \) with \( \theta^0 \)

for each new item arriving sequentially in the task do

obtain the click or not label and use it as a training data

\( \theta^t_{\text{adaptive}} \leftarrow \text{SGD}(\theta^t_{\text{adaptive}}; D^t_{\text{train}}, \alpha) \)

end for

end for

\( \theta^0_{\text{adaptive}} \leftarrow \theta^0_{\text{adaptive}} - \beta(\theta^0_{\text{adaptive}} - \theta^t_{\text{adaptive}}) \)

end for

The online meta learning procedure consists of two loops. The outer loop updates the adaptive meta model parameters while keeping the user invariant layers fixed; the inner loop updates the task/user specific parameters. In the beginning of the algorithm, the meta model is initialized with parameters learned in the offline training stage. In each inner loop, for each task arriving sequentially from the target task set, the task model parameters are initialized with meta model parameters. Then for each new item arriving sequentially in the task, the click-or-not label is obtained and the task...
specific model parameters are updated with $k$ SGD steps. In each outer loop, the adaptive parameters $\theta_{\text{adaptive}}^0$ of meta model is updated based on meta-gradient calculated with Eq.(2).

5 Experiments

5.1 Production Dataset

We collected the production datasets from news feed distributed systems for two hours. The data from the first hour is used for offline meta training and those from the second hour for online meta training and testing. Figure 3 shows the histogram distributions of the number of records per user in training and test stages. Both training and test data have four modes (see Figure 3) corresponding to four types of users: active users with around 20 records per session, regular users with around 13 records per session, occasional users with around 7 records per session, and new users with around 3 records per session.

Table 1: Summary of News Feed dataset

| Data      | Train  | Test   |
|-----------|--------|--------|
| Records   | 595140 | 17731  |
| Users     | 57184  | 2020   |
| Average records/user | 10     | 8      |

Table 1 summarizes the collected data, from which we can see that although there are around 595k training data, for each user there are only 10 records in average for training – which is a typical few-shot learning setting. There is no overlap between training and test users. Therefore, this dataset can test both the generalization and fast adaptation capabilities of the proposed algorithm.

5.2 DNN Architecture

For fair comparison, all algorithms use the same neural network architecture (see Figure 4) for training. The network consists of one embedding layer for each input slot feature and three fully connected hidden layers followed by a softmax layer for binary classification. The input consists of 571 slots, encoding the user features(such as age, gender, location) and news item features(such as item-id, title-term, item-category, author-id). Each slot attribute is encoded with an embedding of 16 dimension. The three hidden layers contain 128, 64, 32 hidden units, respectively. The output layer contains two units for binary classification.
5.3 Parameter Settings

We trained the neural networks with around 595k records collected from 57k users and evaluated on 17k records from 2k new users. For our experiments, we used vanilla SGD in both outer (meta model updating) and inner (user model updating) loops. The hyperparameters in our algorithm is fine-tuned based on those reported in Reptile. Figure 5 provides the results of hyperparameter tuning which indicates that when setting the inner iteration to be 3 and learning rate to be 0.02, the proposed algorithm achieves the highest AUC.

![Figure 5: Results for hyperparameter tuning](image)

(a) Results for tuning the number of inner loop iterations  
(b) Results for tuning the inner loop learning rate

Table 2 lists the hyperparameters for our meta learning algorithm.

5.4 Experimental Results

We compared the proposed algorithm with three baselines by running each method five times. The three baseline methods are: base, base+finetune, and meta. base is the method with a unified user
Table 2: Hyper-parameters for meta-learning algorithm

| Parameter                  | Value                      |
|----------------------------|----------------------------|
| Inner learning rate        | 0.02                       |
| Inner batch size           | 4                          |
| Inner iterations           | 5                          |
| Outer learning rate        | linearly annealed from 1.0 to 0.0 |
| Outer batch size during training | 5                      |
| Outer iterations           | 100k                       |

Table 3: Experimental results on Feeds dataset

| Method         | AUC (mean ± std) |
|----------------|------------------|
| base           | 72.24 ± 0.21     |
| base+finetune  | 73.53 ± 0.11     |
| meta           | 74.72 ± 0.09     |
| proposed       | 77.18 ± 0.09     |

We conduct ablation study to find out the contribution from different factors: meta initialization, decoupled fine-tuning, and online meta learning.

The first experiment we conducted is to compare the conventional meta learning method with two baselines. From Figure 6 we can see that base algorithm did not adapt to new user data, and base+finetune tends to overfitting to training data. In comparison, meta converged faster and to a higher AUC, which demonstrates that meta learning does provide a better initialization than two baselines. The second experiment we conducted is to evaluate which network layers should be fixed during online meta learning.

Table 4 reports the experimental results on fixing different network layers, from which we can see that fixing the embedding layer (1st layer) resulted in worst performance and fixing the middle two hidden layers (2nd and 3rd layers) achieved the highest performance. This means that both em-
bedding layer and classifier layer should be finetuned in order to adapt to changing of user attributes and user interests, while the hidden layers are user invariant parameters and can be kept fixed.

The third experiment we conducted is to evaluate the gain we can get from online meta learning by continually updating both meta and user model with training data online. Figure 7 demonstrates that our algorithm improves consistently with additional training examples/iterations during online meta learning stage.

6 Conclusion

In this paper, we examined an import problem in recommendation – user cold start and introduced a two-stage meta learning algorithm to solve it. The differences with other meta learning methods are: (1) we combine an offline meta and an online meta model to get better initialization for streaming coming users; (2) in online meta model, we divide model parameters into fixed and adaptive parts. In this way, the model can capture cross-user invariant and adapt to personal features. Previous meta learning approaches finetune all parameters for each new user, which is both computing and storage expensive. In contrast, our approach enables all user models share user-invariant parameters which saves both storage and time for adapting. Experiments on production data demonstrates that the proposed method converges faster and to a better performance than baseline methods. Meta-training without online finetuning increases the AUC from 72.24% to 74.72% (2.48% absolute improve-
Our algorithm keeps on improving with additional training examples/iterations during online meta training and achieves a further gain of 2.46% absolute improvement comparing with offline meta training. In our future work, we will further study how the proposed approach can deal with catastrophic forgetting while continually adapting to user specific parameters, benefiting from decoupling user invariant parameters from user dependent parameters.

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