Meta-Learning with Adaptive Weighted Loss for Imbalanced Cold-Start Recommendation

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ABSTRACT

Sequential recommenders have made great strides in capturing a user's preferences. Nevertheless, the cold-start recommendation remains a fundamental challenge in which only a few user-item interactions are available for personalization. Gradient-based metalearning approaches have recently emerged in the sequential recommendation field due to their fast adaptation and easy-to-integrate abilities. The meta-learning algorithms formulate the cold-start recommendation as a few-shot learning problem, where each user is represented as a task to be adapted. However, while meta-learning algorithms generally assume that task-wise samples are evenly distributed over classes or values, user-item interactions are not that way in real-world applications (e.g., watching favorite videos multiple times, leaving only good ratings and no bad ones). As a result, in the real-world, imbalanced user feedback that accounts for most task training data may dominate the user adaptation and prevent meta-learning algorithms from learning meaningful metaknowledge for personalized recommendations. To alleviate this limitation, we propose a novel sequential recommendation framework based on gradient-based meta-learning that captures the imbalance of each user's rating distribution and accordingly computes adaptive loss for user-specific learning. It is the first work to tackle the impact of imbalanced ratings in cold-start sequential recommendation scenarios. We design adaptive weighted loss and improve the existing meta-learning algorithms for state-of-the-art sequential recommendation methods. Extensive experiments conducted on real-world datasets demonstrate the effectiveness of our framework.

CCS CONCEPTS

• Information systems \rightarrow Recommender systems; • Computing methodologies \rightarrow Learning latent representations.

KEYWORDS

Sequential Recommender Systems, Cold-Start Recommendation, Imbalanced Data, Meta-Learning, Loss Function

1 INTRODUCTION

When modeling a user's dynamic preferences, temporal user-item information plays an important role. For this reason, sequential recommender systems have continuously evolved in the field of recommendation systems [5, 26]. Sequence models leverage temporal information and excel at compressing the user's historical behaviors to a single representation [19]. However, since sequential

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(a) Imbalanced Rating Distribution

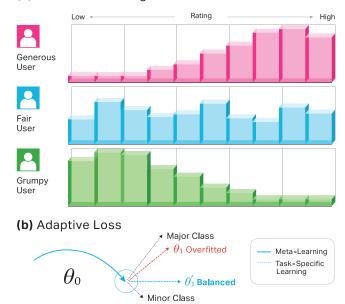


Figure 1: The concept of our method. (a) Individual users have various rating distributions. The mean, variance, and skewness are different in each case. (b) Adaptive weighted loss corrects inner-loop adaptation path for each user. We expect minor classes could be considered more for task-specific learning to prevent overfitting.

recommender systems mainly rely on the total number of historical interactions, they are fragile to the cold-start problem, where user-item interactions are too short that only limited user information is available [31].

When new users come to an online service (e.g., e-commerce, streaming services), it is a significant moment that determines the sustainability of a business with them. The users decide whether or not to continue using the service within a few initial actions. For example, if they are initially unsatisfied with the quality of service, they can quickly move to another service. In addition, as privacy becomes a primary concern, more and more users are reluctant to disclose their information. Therefore, the user cold-start recommendation is inevitable and essential in a business competitive environment.

Recently, various studies have widely adopted gradient-based meta-learning algorithms, such as model-agnostic meta-learning (MAML) [6], in recommendation systems. It has the advantage of being smoothly incorporated with existing recommender networks optimized by gradient descent. The basic idea behind meta-learning

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in recommendation systems is to formulate the user cold-start recommendation as a few-shot learning problem and train the model to adapt to new (i.e., unseen) users rapidly. MeLU [17] integrates user and item attributes with the MAML algorithm, and MAMO [4] further uses task-specific and feature-specific memories to keep individual users' preferences. MetaCSR [12] incorporates the gradient-based meta-learner and the diffusion representer that is composed of graph convolutional networks (GCNs) [16] to model high-order user-item correlation without side information (e.g., age, job). So far, various meta-learning approaches have effectively improved the cold-start recommendation performance.

In a general setting, the MAML algorithm supposes that the number of examples per class is fixed (i.e., N-way k-shot setting). However, as shown in Figure 1, each user has user-wise criteria for rating items in real-world situations. As a result, user ratings are not uniformly distributed (i.e., imbalanced). It may cause an overand under-fitting problem, which prevents the model from learning meaningful meta-knowledge [18]. In the meantime, studies on sequential recommender systems have mainly focused on users' implicit feedback (e.g., clicks, views) rather than explicit feedback (e.g., ratings, likes) [11]. Therefore, the negative impact of imbalanced rating distribution on sequential recommendation performance is an unexplored topic to study. In this work, we simultaneously utilize implicit and explicit feedback (i.e., multi-behavior data) to have a holistic view of user behavior. However, much explicit feedback is imbalanced or noisy in real-world applications, which corrupts and dominates the learning process. It is challenging to judge which feedback is helpful or not with only a tiny amount of information in cold-start scenarios.

To alleviate such problems, we propose a novel MEta-learning based sequential recommender with adaptive weighted LOss for imbalanced cold-start recommendation (MELO). Specifically, we have improved existing meta-learning based sequential recommendation methods for the user cold-start problem by handling the rating imbalance problem with our proposed adaptive loss. Our framework consists of (1) the sequential recommender modeling temporal dynamics in user-item interactions, (2) the gradient-based meta-learner that makes the recommender quickly adapt to individual users by observing only a few interactions, and (3) the adaptive weighted loss, which dynamically adjusts the importance of each interaction during the user adaptation process by capturing the task state.

The main contribution of this work is summarized as follows:

- It is the first work to tackle the negative impact of imbalanced rating distribution in real-world cold-start recommendation scenarios.
- We propose the adaptive weighted loss that recognizes the rating imbalance based on temporal dynamics and corrects the learning path during the meta-learning process.
- Our framework can be easily integrated with any existing sequential recommendation models, such as GRU4Rec, NARM, SASRec, and BERT4Rec.
- We extensively validate our framework with existing sequential recommenders on real-world datasets to demonstrate the effectiveness of our proposal.

2 RELATED WORK

2.1 Sequential Recommendation

Over the past few years, state-of-the-art sequential recommender systems have tried to model user-item interactions and focus on understanding a users' preferences [26]. GRU4Rec [9] learns the contextual relationship between users and items in the sequence through GRU layers. NARM [19] similarly incorporates an attention mechanism into GRU architectures. SASRec [14] brings transformer architectures to build higher-capacity models. BERT4Rec [24] employs a bidirectional encoder and masked training techniques to improve unidirectional transformer models.

There are two types of user feedback data for the recommendation system: implicit and explicit [8]. Implicit feedback is information obtained indirectly by monitoring users' behavior, such as item clicks and page views. On the other hand, explicit feedback is a response obtained directly from users according to their preferences for a product, such as ratings and likes. Sequential recommender systems can model users' indirect behavior, and most sequential recommender research has targeted implicit feedback only. Meanwhile, recent studies utilizing multi-behavior data (i.e., both implicit and explicit feedback) to construct comprehensive understanding of users are emerging [7, 13]. In this work, we propose a novel method to mitigate the imbalanced distribution of explicit user ratings while modeling the temporal dynamics of implicit user-item interaction through the sequence model.

2.2 Meta-Learning for Cold-Start Problem

The core idea of recommendation systems with gradient-based meta-learning is to learn the meta-knowledge that initializes the model parameter for personalized recommendation. MeLU [17] leverages side information with the MAML algorithm [6]. They locally update the decision-making layer based on each user's pattern and globally update user-item embeddings and whole layers. MAMO [4] designs two memory networks and guides the global sharing initialization parameter not to fall into the local optima of irregular users. The feature-specific memory helps to initialize the recommender model, and the task-specific memory guides the prediction process. MetaCSR [12] incorporates high-order embeddings of user-item generated by graph neural networks and the gradient-based meta-learning algorithm to extract sharable knowledge of prior users. Mecos [31] encodes sequence pairs and trains the matching network to connect the target item to potential users. They present a practical approach for the item cold-start problem in the field of sequential recommendation. As mentioned above, recent works propose various meta-learning based approaches for the cold-start recommendation. However, most approaches do not seriously consider the imbalance of rating distribution, which easily varies from one user to another during the inner-loop optimization process. In this work, we highlight the importance of recognizing the imbalanced rating distribution and propose the adaptive weighted loss to accordingly and dynamically calibrate the learning process.

2.3 Meta-Learning for Imbalanced Problem

The imbalance data generally degrades the learning quality, and research on meta-learning for the imbalanced problem is attracting attention. MeTAL [2] proposes a learnable way to train a loss function to achieve better generalization for problems in various applications. The loss function network computes task-adaptive loss with embeddings generated by the task state network. The two neural networks are optimized each time during an outer-loop update. Bayesian TAML [18] introduces three learnable variables to scale the loss function. They process statistical information such as the mean, variance, and cardinality for the input of balancing variable networks. They also design the variational inference framework to alleviate the randomness of statistical values. PALM [29] proposes a top-K nearest neighbor search to obtain different learning rates for individual users. A tree-based method and a memory-agnostic regularizer are employed to increase the efficiency of search and storage operations. ATS [28] introduces a neural task scheduler that identifies informative tasks (i.e., excluding noisy labels) for the task adaptation process. They suggest two input features, which represent the characteristics of a candidate task, to avoid the effort of finding the optimal combination heuristically. Overall, the above studies propose various learnable ways to adjust the loss values to train the model correctly. However, the proposed methods either use complex networks (e.g., many inputs and parameters) or expensive algorithms (e.g., search and sort) to compute. In this work, we suggest a more straightforward and automated way to adjust the loss function by sample-wise adaptive weights computed in a sequence manner.

3 PRELIMINARY

3.1 Problem Formulation

The sequential recommendation task assumes $\mathcal{U} = \{u_1, u_2, \ldots, u_n\}$ as a set of users and $\mathcal{V} = \{v_1, v_2, \ldots, v_m\}$ as a set of items, where n and m are respectively the number of users and items. A sequence of user-item interactions generated by user $u_i \in \mathcal{U}$ is represented as $X_i = \{v_1^i, v_2^i, \ldots, v_t^i\}$ in chronological order at time step t. Here, t denotes the interaction order rather than the absolute timestamp, similar to previous works [14, 27]. In a rating prediction task, let $Y_i = \{y_1^i, y_2^i, \cdots, y_t^i\}$ be denoted as a set of ratings for each item $v^i \in X_i$. In this work, our goal is to correctly predict the rating score y_{t+1}^i of the next-item v_{t+1}^i based on the past sequences X_i and Y_i , and we formulate this problem as a regression task.

3.2 Meta-Learning

MAML [6] is a gradient-based meta-learning algorithm for fast task adaptation, particularly few-shot learning problems. It can be easily integrated with any neural networks optimized by gradient descent. In this work, we assume that each user u is a task \mathcal{T}_i drawn from a task distribution $p(\mathcal{T})$. Each task \mathcal{T}_i consists of two disjoint sets; support set and query set. The support set $\mathcal{D}_i^S = \{X_i^S, Y_i^S\}$ is used for inner-loop optimization (i.e., task / user adaptation), and the query set $\mathcal{D}_i^Q = \{X_i^Q, Y_i^Q\}$ is used for outer-loop optimization (i.e., meta-optimization). Based on this setting, our goal is to meta-learn desirable initial parameters of a given sequential recommender

network that make the recommender quickly adapt to cold-start new users with a limited number of user-item interactions.

4 METHODOLOGY

We present the overall framework in Algorithm 1 and Figure 2. We first introduce a meta-learner that allows sequential recommenders to be adapted to cold-start users and show how it can be easily integrated with any sequential recommenders based on neural networks. Next, we propose our adaptive weighted loss to dynamically calibrate the learning process according to the imbalanced rating distribution.

4.1 Meta-Learner

Let us assume that we have a sequential recommender network f_θ , and our goal is to learn a proper parameter initialization $\theta(=\theta_{i,0})$ that allows the network f_θ to make fast adaptation to cold-start users with a few numbers of user-item interactions. We make this happen by introducing a meta-learner based on the MAML algorithm, which can be easily integrated with any neural network model optimized by gradient descent. The MAML algorithm performs bi-level optimization, which consists of local update (i.e., task / user adaptation) and global update (i.e., meta-optimization). We define the learnable initialization $\theta(=\theta_{i,0})$ as meta-knowledge, and it is updated to task-wise (i.e., each user) model parameters $\theta_{i,j}$ for each task \mathcal{T}_i during the local update. The local update is also known as the inner-loop optimization process in that we conduct j-step gradient updates with the training (i.e., support) dataset \mathcal{D}_i^S as:

$$\theta_{i,j} = \theta_{i,j-1} - \alpha \nabla_{\theta_{i,j-1}} \mathcal{L}(\mathcal{D}_i^S; \theta_{i,j-1}), \tag{1}$$

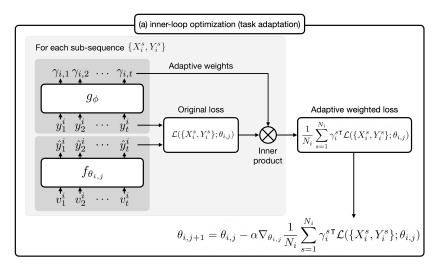
where α is the step size for the inner loop gradient-based optimization.

Each task-specific model $f_{\theta_{i,J}}$ is obtainable through J-step of gradient updates, and then it is evaluated with unseen query examples \mathcal{D}_i^Q for the task \mathcal{T}_i in the outer-loop to properly find the generalized initialization θ (i.e., meta-parameter). We then express the outer-loop optimization process as:

$$\theta \leftarrow \theta - \beta \nabla_{\theta} \sum_{\mathcal{T}_i} \mathcal{L}(\mathcal{D}_i^Q; \theta_{i,J}),$$
 (2)

where we aggregate multiple task-wise query losses to compute the gradient with respect to the initialization θ , and β is the step size for the outer loop gradient-based optimization.

To further improve generalization in meta-learning, we correctly split the overall user-item interactions (i.e., user-level sequence data) for task adaptation and meta-optimization, which correspond to support and query sets, respectively. For each user u_i , we hold out the next interaction v_{t+1}^i at time step t+1 and assign a sequence $\{v_1^i, v_2^i, \ldots, v_{t+1}^i\}$, which includes it as the last item, to the query set \mathcal{D}_i^O to evaluate the task-specific parameter $\theta_{i,J}$ in the outer-loop. On the other hand, we differently allocate the other sequence $\{v_1^i, v_2^i, \ldots, v_t^i\}$, which ends before the held-out interaction at time step t+1, to the support set \mathcal{D}_i^S , and this is mainly used to fine-tune the model in the inner-loop. Each example in both \mathcal{D}_i^S and \mathcal{D}_i^O is generated using the data augmentation technique of previous studies [12, 21, 25]. For example, let the assigned full sequence of items in the support set be X_i^S , then it is sliced into N_i consecutive



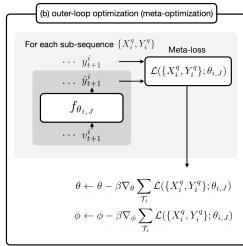


Figure 2: Overveiw of MELO framework. (a) The sequential recommender $f_{\theta_{i,j}}$ receives item sequences and predicts ratings. The task state recurrent encoder g_{ϕ_i} receives rating sequences and outputs adaptive weights. Each original (adaptation) loss is multiplied by each weight to calculate the adaptive weighted loss. Then, it locally updates $\theta_{i,j}$ for J times. (b) Both θ and ϕ are evaluated by the query set and globally updated in the outer-loop.

sub-sequences $X_i^s \in X_i^S$: $\{v_1^i, v_2^i\}$, $\{v_1^i, v_2^i, v_3^i\}$, . . . , $\{v_1^i, v_2^i, \ldots, v_t^i\}$. On the contrary, we apply the slicing technique in reverse order to in reverse order to the query set X_i^Q to generalize meta-knowledge θ based on the held-out next-item: $\{v_t^i, v_{t+1}^i\}$, $\{v_{t-1}^i, v_t^i, v_{t+1}^i\}$, . . . , $\{v_1^i, \ldots, v_t^i, v_{t+1}^i\}$.

4.2 Adaptive Weighted Loss

In general, MAML assumes that the number of instances per class does not vary (i.e., *N*-way *k*-shot setting). This setting limits the model to properly utilize the learned meta-knowledge when the number of instances is disproportionate (i.e., imbalanced) in a given task. Therefore, in this work, we aim to build sequential recommender systems that can adapt to cold-start users by incorporating the MAML algorithm and further rightly understand the state of imbalance distribution in each cold-start user and appropriately modify the learning process to prevent overfitting and achieve a good generalization. To do so, it is crucial to ensure that the samplewise gradients are well-aligned without being overwhelmed by each other [30]. We implement this by assigning an adaptive weight (i.e., gradient step size) to each sub-sequence loss.

To adaptively correct the learning path of imbalanced problems with the MAML-based sequential recommender systems, we employ the task state recurrent encoder that can effectively aggregate the state of rating distribution based on temporal dynamics in each task. Our proposed recurrent encoder g_{ϕ} meta-learns representation of the rating sub-sequence $Y_i^s \in Y_i^S$ by updating a recurrent hidden state vector h_t^i and further outputs the adaptive weight values $\gamma_i^s \in \mathbb{R}^{|Y_i^s|}_{\geq 0}$ to correct the original inner-loop loss (i.e., adaptation). For each item v_t^i in the sub-sequence Y_i^s , the recurrent cell $\hat{g}_{\phi^{\text{cell}}}$ updates the hidden state vector h_t^i from the previous ones with its rating score y_t^i , and the adaptive weight $\gamma_{i,t}$ is computed by

transforming the hidden state vector as:

$$\gamma_{i,t} = \tilde{g}_{\phi^{\text{out}}}(h_t^i) \in \mathbb{R}_{\geq 0}, \quad h_t^i = \hat{g}_{\phi^{\text{cell}}}(y_t^i; h_{t-1}^i),$$
(3)

where the function $\tilde{g}_{\phi^{\text{out}}}$ is a linear mapping, which aligns item-wise gradients without being crushed by each other, and we compute the adaptive weights $\gamma_i^s = \left[\gamma_{i,1}, \gamma_{i,2}, \ldots, \gamma_{i,|\mathbf{Y}_i^s|}\right]^T$ for all items in the subsequence \mathbf{Y}_i^s . This overall process can be expressed as $\gamma_i^s = g_{\phi}(\mathbf{Y}_i^s)$, and the encoder g_{ϕ} is only updated in the outer-loop as metaknowledge that is shared over all tasks without any adaptation.

The original adaptation loss of each sub-sequence $\{X_i^s, Y_i^s\}$ is defined by $\mathcal{L}(\{X_i^s, Y_i^s\}; \theta_{i,j})$, and it is a vector composed of item-wise loss values. We correct the original adaptation loss by adaptively weighting item-wise loss values and obtain the modified loss to adapt appropriately to imbalanced problems. As both the adaptive weights γ_i^s and the original adaptation loss values $\mathcal{L}(\{X_i^s, Y_i^s\}; \theta_{i,j})$ are equally defined over given items in the sub-sequence X_i^s (and Y_i^s), we do inner product between them to aggregate the modified loss values and repeat this over all existing N_i sub-sequences. That way, we accordingly run each inner-loop update as:

$$\theta_{i,j+1} = \theta_{i,j} - \alpha \nabla_{\theta_{i,j}} \frac{1}{N_i} \sum_{s=1}^{N_i} \gamma_i^{s \mathsf{T}} \mathcal{L}(\{X_i^s, Y_i^s\}; \theta_{i,j})$$
(4)

4.3 Encoder Architecture

The role of the task state recurrent encoder is to interpret the rating distribution and convey valuable information to the recommender network, which learns the interaction between items and ratings. One natural way to model the user rating information is to use hand-designed features. MeTAL [2] preprocesses task information for its inputs (e.g., the mean of predictions and labels) and employs a 2-layer MLP that returns a scalar value as output. Bayesian TAML [18] uses a bayesian inference network using the statistics pooling technique with the mean, variance, and cardinality. However, this

Algorithm 1 MELO

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Require: p(\mathcal{T}): distribution over tasks
Require: \alpha, \beta: step size hyperparameters
Require: Sequential recommender network f_{\theta}
Require: Task state encoder network g_{\phi}
   1: Randomly initialize \theta, \phi
   2: while not done do
            Sample a batch of tasks \mathcal{T}_i \sim p(\mathcal{T})
   3:
            for all \mathcal{T}_i do
   4:
                Sample \{X_i^S, Y_i^S\} sequences as support set \mathcal{D}_i^S and \{X_i^Q, Y_i^Q\} sequences as query set \mathcal{D}_i^Q from \mathcal{T}_i
Initialize adapted parameters \theta_{i,0} = \theta
   5:
   6:
                 for inner-loop updates j = 0 : J - 1 do
   7:
                      Compute the original inner loss on each sub-sequence:
   8:
                      \{\mathcal{L}(\{X_i^s, Y_i^s\}; \theta_{i,j})\}_{s=1}^{N_i}
                      Compute the adaptive weight on each rating sequence:
   9:
                      \{\gamma_i^s = g_\phi(Y_i^s)\}_{s=1}^{N_i}
                      Compute the adaptive weighted loss:
 10:
                      \begin{split} \tilde{\mathcal{L}}(\mathcal{D}_{i}^{S};\theta_{i,j}) &= \frac{1}{N_{i}} \sum_{s=1}^{N_{i}} \gamma_{i}^{s \, \tau} \mathcal{L}(\{X_{i}^{s}, Y_{i}^{s}\};\theta_{i,j}) \\ \text{update } \theta_{i,j} \text{ for task adaptation:} \end{split}
 11:
                      \theta_{i,j+1} = \theta_{i,j} - \alpha \nabla_{\theta_{i,j}} \tilde{\mathcal{L}}(\mathcal{D}_i^S; \theta_{i,j})
 12:
                 Compute the outer loss on the query set:
 13:
                 \mathcal{L}(\mathcal{D}_{i}^{Q};\theta_{i.I})
 14:
            update (\theta,\phi) for meta-optimization:
 15:
            \theta \leftarrow \theta - \beta \nabla_{\theta} \sum_{\mathcal{T}_i} \mathcal{L}(\mathcal{D}_i^{\bar{Q}}; \theta_{i,J})
            \phi \leftarrow \phi - \beta \nabla_{\phi} \sum_{\mathcal{T}_i} \mathcal{L}(\mathcal{D}_i^Q; \theta_{i,J})
 16: end while
```

bayesian inference network has a complex structure and sometimes incurs unnecessary computation.

Our proposed encoder sequentially receives user-item ratings over multiple time steps and refines them to an informative representation without any preprocessed statistics and complex networks. When the encoder takes a user-item sequence, it measures the importance of each rating based on the current state. Then, it outputs item-wise weights to balance the original loss value during the inner-loop updates adaptively. The recurrent structure tells the encoder which items to focus on based on its temporal dynamics and effectively resolves the need for additional preprocessed information. Furthermore, our encoder does not contain any constraints, so it is easily adapted to any recommendation scenario. The performance comparison of task state encoders is illustrated in the experimental section 5.3.

5 EXPERIMENTS

We conduct comprehensive experiments to evaluate the proposed method on four real-world datasets. Our goal is to address the following research questions (RQs):

- **RQ1**: How much does MELO improve the performance of state-of-the-art sequential recommenders? (Section 5.2)
- RQ2: How do different loss functions affect the cold-start recommendation performance? (Section 5.3)

Table 1: Dataset statistics after preprocessing

	Grocery	Sports	Yelp	Movie
#Users	58,035	67,523	41,365	6,040
#Items	4,776	13,448	1,221	2,514
#Ratings	475,247	721,498	445,070	977,839
Average length ¹	8.0	10.7	10.8	29.2
Balance score	0.57	0.60	0.85	0.90

¹ The maximum sequence length of a user is 30.

- RQ3: How robust is MELO to the cold-start problem with extremely short sequences? (Section 5.4)
- RQ4: How much does MELO reduce the high computational cost of the MAML algorithm? (Section 5.5)
- RQ5: How does each component of MELO affect the framework? (Section 5.6)
- RQ6: How well does MELO predict the ratings of different user types? (Section 5.7)

5.1 Experimental Setup

- 5.1.1 **Datasets.** In this work, we use four public datasets containing users' 1-5 scale rating information on items. Each dataset differs in size and degree of rating imbalance. We assume a cold-start situation with a lack of user information, so we mainly select a small-sized dataset with fewer than 1 million records.
 - **Grocery**: This dataset contains the "Grocery" category of product reviews from Amazon.com [23]. It has the most disproportionate ratings and the shortest sequence length. The proportion of each rating score is as follows: 5 (**72.8**%), 4 (13.4%), 3 (6.7%), 2 (3.8%), 1 (3.3%).
 - **Sports**: This dataset comprises the "Sports" category of product reviews from Amazon.com [23]. It has more users, items, and ratings than the Grocery category. The proportion of each rating score is as follows: 5 (**69.4%**), 4 (<u>18.0%</u>), 3 (7.0%), 2 (2.9%), 1 (2.7%).
 - Yelp: This dataset includes users, businesses, and reviews from the Yelp dataset challenge. The proportion of each rating score is as follows: 5 (35.5%), 4 (35.2%), 3 (17.2%), 2 (7.8%), 1 (4.3%).
 - Movie: GroupLens Research collected movie reviews from the MovieLens service. We adopt "MovieLens 1M" dataset. The proportion of each rating score is as follows: 5 (36.2%), 4 (31.7%), 3 (16.0%), 2 (8.8%), 1 (7.3%).

We preprocess the dataset to set a user cold-start scenario: (1) Additional information, such as age and category, is removed. Only user id, item id, rating, and timestamp information are left, representing cold-start users and their imbalanced rating distribution. (2) Items with less than 50 ratings are removed, which causes the item cold-start problem, which is not the main research topic of this study. (3) We build a user-item interaction sequence in chronological order and remove the timestamp feature afterward.

In quantifying the degree of imbalance, we use the Shannon entropy H to measure the balance of rating distribution. For example, let a dataset have n instances and k classes of size c_i , then H is calculated as $\log k$ when the size of all classes are equal $\frac{n}{L}$.

Therefore, we can express the Balance score as follows:

$$Balance = \frac{H}{\log k} = \frac{-\sum_{i=1}^{k} \frac{c_i}{n} \log \frac{c_i}{n}}{\log k}$$
 (5)

The balance score is closer to 0 when the dataset is imbalanced and equal to 1 when the dataset is entirely balanced. For example, the Grocery dataset is highly skewed, and its balance score is 0.57. In Table 1, we present the statistics of each preprocessed dataset.

5.1.2 **Evaluation Metrics.** To evaluate the experimental results for the proposed method, we adopt Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE), which are standard metrics that address how close the predicted ratings are to the actual user ratings [3]. The two metrics, RMSE and MAE, are complementary. RMSE disproportionately penalizes significant errors by squaring the residuals. As a result, it is more affected by wrong predictions. On the other hand, MAE weighs large and small errors equally. Therefore, it is preferred when outliers do not severely impact the objective.

Since the imbalanced distribution causes a large variance, we conduct performance evaluations focusing on RMSE. If we predict with one single score that accounts for the most, MAE can be pretty low, but RMSE is not. For example, MAE is 0.5140 if we predict all outcomes as a score of 5 in the Grocery dataset, which is lower than the score predicted by the proposed method. However, RMSE will be 1.1278 due to being penalized by a significant deviation.

- *5.1.3* **Baselines.** We reproduce the following representative sequential recommenders for a rating prediction task to verify the effectiveness of the proposed method.
 - **GRU4Rec** [9]: It uses Gated Recurrent Unit (GRU) to encode user-item interaction records into a representation vector for the session-based recommendation. The original GRU4Rec is used with an additional linear projection layer to produce a rating value
 - NARM [19]: It integrates the GRU-based local and global encoder with the attention mechanism to capture the user's primary purpose in the current session. Instead of concatenating local and global contexts as in the original paper, we multiply them and add a linear projection layer.
 - **SASRec** [14]: It employs the unidirectional transformerbased method with single-head attention for the sequential recommendation. The original SASRec is used with an additional linear projection layer to produce a rating value.
 - BERT4Rec [24]: It uses the bidirectional multi-head selfattention architecture to effectively model sequential patterns in user-item interaction. The original BERT4Rec is used with an additional linear projection layer to produce a rating value.
- 5.1.4 **Implementation Details.** Sequential recommender baselines are implemented with reference to the codes published by the authors. We use simple dictionary embedding with embedding matrix $W \in \mathbb{R}^{m \times d_v}$ for all baseline models, where m denotes the number of items and d_v denotes the dimension size of embedding. Positional embedding is added for SASRec and BERT4Rec.

Our meta-learner is implemented with PyTorch referring to MAML [6] and MAML++ [1]. We divide users into non-overlapping

partitions for training, validation, and test sets. The maximum user-item sequence length used in this experiment is 30 to create cold-start situations. The user sequence selected as the task is split into 25 examples of support set and 3 examples of query set. We use MSE for the original loss function, and the number of inner-loop steps *J* is 3 in default. We use LSTM cells [10] for our recurrent encoder, which is composed of rating embedding with a dimension size of 16 and a hidden state dimension of 32. We normalize all ratings between 0 and 1, and clip the gradients to prevent the gradient explosion. A cosine annealing schedule is applied along with the Adam [15] optimizer. We train 32,000 episodes for the Movie dataset and 48,000 for the Grocery, Sports, and yelp datasets. For evaluation, we use 600 episodes for validation and 1,000 episodes for the test. We perform 5 independent experiments for all baselines and report the average value. Our code contains all the details on every baseline architecture and hyperparameter.¹

5.2 Overall Results (RQ1)

Table 2 summarizes the experimental results with all baseline methods: Basic, MAML, and MELO integration. MELO effectively integrates state-of-the-art sequential recommender methods, and the average performance of MELO integrations over Basics and MAML improves across all datasets.

Specifically, the most performance improvement is when the dataset has a severe imbalance or a short sequence length, such as the Grocery, Sports, and Yelp datasets. In particular, MELO shows the most significant performance improvement compared to MAML in the Grocery dataset, which has the most imbalanced distribution with 72.8% ratings clustered into a score of 5 and an average sequence length of 8. In addition, although MAML's performance is worse than Basic's on the Yelp dataset, MELO outperforms both. From this result, we could infer that the proposed adaptive loss makes the gradient-based meta-learning method more robust to various real-world situations.

On the other hand, when the degree of imbalance is less and the sequence length is long enough, the performance improvement is not significant between the existing MAML algorithm and MELO. For example, the Movie dataset with a balance score of 0.9 (i.e., relatively balanced) and an average sequence length of 29.2 (i.e., relatively long) shows a slight performance improvement. We will further examine the Movie dataset in terms of the performance impact of different sequence lengths in section 5.4.

The overall experimental results suggest that the contribution of the adaptive loss becomes greater when faced with less and less user information (i.e., cold-start situation). Given that MELO's performance is statistically superior or equivalent to other methods in most cases, MELO is available as a standard solution for various user cold-start scenarios.

5.3 Loss Function (RQ2)

To better understand the role of the loss function, we conduct a comparative experiment with three different ways of generating the adaptive loss function: Focal, Stats, and Ours (i.e., adaptive weighted loss). We use BERT4Rec as a base recommender for this

 $^{^{1}}https://github.com/YangYongJin/MELO\\$

Table 2: Performance comparison of sequential recommender methods with or without MAML and MELO integration. Bold represents the best variant in each sequential recommender, and <u>underlined</u> indicates the second best variant. Note that * denotes improvement over the second-best variant with p-value < 0.05 (measured by t-test with 5 independent trials.)

	Avg.	Balance	e Metric	GRU4Rec		NARM		SASRec		1	BERT4Rec		Improv. Improv.						
	length			Basic	MAML	MELO	Basic	MAML	MELO	Basic	MAML	MELO	Basic	MAML	MELO		over MAML ²		
Grocery	Grocery 8.0	0.57	RMSE	1.0794	1.0293	0.9859*	1.0804	1.0176	0.9935*	1.0911	1.0651	0.9949*	1.0907	1.0501	0.9925*	8.63%	4.67%		
Grocery			MAE	0.7797	0.6890	0.6700*	0.7927	0.6811	0.6743*	0.8003	0.7352	0.6724^{*}	0.7971	0.6803	0.6608*	15.53%	3.79%		
Sports	10.7	0.60	RMSE	1.0364	1.0147	0.9710*	1.0373	1.0007	0.9667*	1.0360	1.0134	0.9690*	1.0332	1.0041	0.9565*	6.75%	4.21%		
Sports	10.7		MAE	0.7518	0.6987	0.6765*	0.7837	0.6887	0.6627*	0.7558	0.6695	0.6624	0.7656	0.6820	0.6464*	13.34%	3.31%		
Yelp	10.8	.8 0.85	RMSE	1.2084	1.2396	1.2005	1.2156	1.2154	1.2049*	1.2374	1.2540	1.1931*	1.2422	1.2610	1.1777*	2.58%	3.87%		
1етр 10.8	10.0	10.0	10.0	0.83	MAE	0.9765	0.9994	0.9666*	0.9719	0.9825	0.9688	0.9841	1.0008	0.9591*	0.9919	1.0106	0.9431*	2.20%	3.88%
Movie 29.2	20.2	0.90	RMSE	0.9937	0.9856	0.9725*	0.9939	0.9818	0.9733*	0.9944	0.9761	0.9675	0.9990	0.9755	0.9750	2.33%	0.78%		
	29.2	29.2	0.90	MAE	0.7930	0.7744	0.7674	0.7943	0.7666	0.7702	0.7929	0.7642	0.7602	0.7991	0.7617	0.7685	3.55%	0.02%	

¹ The average improvement over Basic baselines

experiment. Table 3 displays the performance of three different loss functions.

In this experiment, we transform the Focal loss equation for a regression task (i.e., a rating prediction task) with the regularized MSE loss based on the previous study [22]. The Focal loss [20] decreases the relative loss for easy and correct examples but focuses on learning hard and incorrect examples. The scaling factor of the Focal loss downsizes the contribution of easy examples by dynamically reducing cross-entropy loss during training. However, baselines applied with the Focal loss do not improve the performance but rather deteriorate. This result implies that a fixed re-weighting strategy by counting the number of easy and hard examples in the dataset cannot achieve user-level optimization.

Next, we conduct a comparative experiment with the Stats loss, which processes statistical features from the user-item sequence and provides further information to the recommender model. The Stats encoder is built with a 2-layer MLP referring to the previous study [2]. The statistical information of the target sequence, such as mean, variance, and cardinality, is preprocessed separately and put into the stats encoder network as input. Since each dataset has its cold-start characteristic, the preprocessing process becomes complex and domain knowledge dependent. Table 4 shows the best-performing combinations on the datasets.

Our adaptive weighted loss achieves comparable performance to the Stats loss. This result demonstrates that the representation modeled by our recurrent encoder has sufficient information compared to manually designed statistics. It allows us to compute adaptive weights more concisely without increasing the complexity of the network and aggregating additional information. Furthermore, our encoder models the user's rating sequentially, and the representation can be updated efficiently as new user information continuously arrives (e.g., online service). However, the Stats encoder requires a batch of samples to extract user information properly. In summary, individual user behavior modeling is essential and beneficial for calculating adaptive loss to improve personalized

Table 3: Impact of different loss functions

Dataset	Metric	Focal	Stats ¹	Ours
Grocery	RMSE	1.0390	0.9927	0.9925
Grocery	MAE	0.6918	0.6611	0.6608
Sports	RMSE	1.0171	0.9569	0.9565
эрогиз	MAE	0.7054	0.6326	0.6464
Yelp	RMSE	1.2586	1.1781	1.1777
теф	MAE	1.0238	0.9438	0.9431
Movie	RMSE	0.9833	0.9746	0.9750
Movie	MAE	0.7700	0.7663	0.7685

 $^{^{1}}$ The result is from the best-performing combination of Table 4.

recommendation accuracy. Our adaptive weighted loss shows generalized performance over multiple users and datasets.

5.4 Severe Cold-Start Problem (RQ3)

We study the effectiveness of MELO under severe cold-start conditions. We choose the Movie dataset because its average sequence length is 29.2, the longest among the datasets (The maximum sequence length taken by MELO is 30). On the other hand, the average length of the other datasets is less than 10.8, a difference of approximately 20 from the Movie dataset. Sufficient length suggests that various examples may exist depending on the sequence length. Therefore, in this experiment, we randomly slice a sequence length from 5 to T to generate diverse cold-start situations. As T decreases, the percentage of severe cold-start users increases.

Table 5 illustrates the prediction performance of BERT4Rec with MELO and MAML integration on different maximum lengths T. The result shows that the performance improvement of MELO over

² The average improvement over MAML integrations

Table 4: Performance of the Stats loss on different combinations of input features. Bold represents the best result on each dataset.

Feature	Metric	Grocery	Sports	Yelp	Movie
(1) All features	RMSE	0.9940	0.9704	1.1881	0.9785
(2) No mean	RMSE	1.0076	0.9649	1.1781	0.9840
(3) No std	RMSE	0.9927	0.9709	1.1926	0.9746
(4) No label ¹	RMSE	1.0050	0.9661	1.1911	0.9817
(5) No pred ²	RMSE	0.9984	0.9569	1.1844	0.9773
(6) No loss ³	RMSE	0.9959	0.9663	1.1950	0.9753
(2) + (3)	RMSE	1.0336	0.9610	1.2005	0.9765
(4) + (5) + (6)	RMSE	1.0488	0.9868	1.1968	0.9871

 $^{^{1}}$ The true rating distribution of the sub-sequence \mathbf{Y}_{i}^{s}

Table 5: Performance with different maximum sequence length T on the Movie dataset. Bold represents the best improvement by MELO among different sequence lengths, and underlined indicates the second best improvement.

Metric	Method	10	15	20	25	30
	MAML	0.9879	0.9802	0.9772	0.9806	0.9623
RMSE	MELO	0.9629	0.9674	0.9599	0.9677	0.9581
	Improv.	2.53%	1.31%	1.77%	1.31%	0.44%
MAE .	MAML	0.7772	0.7712	0.7649	0.7709	0.7545
	MELO	0.7647	0.7671	0.7634	0.7688	0.7578
	Improv.	1.61%	0.53%	0.20%	0.27%	-0.43%

MAML integration increases as the maximum length T decreases. It implies that MELO is versatile under very challenging conditions, where the maximum sequence is only a length of 10, and all sequences lie between 5 and 10. In other words, short-length sequences are problematic for MAML integration alone. We may assume that adaptive loss affects the model to avoid over- and under-fitting with a small amount of interaction. This effect helps the recommender model to find a valid path to imbalanced cold-start users.

5.5 Model Efficiency (RQ4)

We now study how much MELO reduces the computational cost of the existing MAML algorithm. We observe that MELO improves the performance even in cases with one-step inner loop updates. Figure 3 illustrates the performance of MELO and MAML integrated with BERT4Rec when the inner-loop step varies on each dataset. The RMSE and MAE values rapidly decrease after a single update, and MELO reaches its best performance with only one iteration. This result may suggest that the adaptive loss function propagates a sufficient amount of loss to the recommender network during

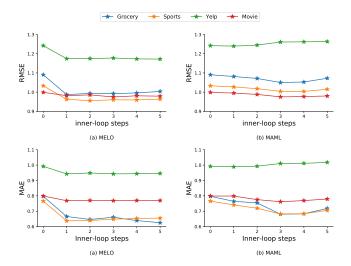


Figure 3: The performance of (a) MELO and (b) MAML according to the number of inner-loop steps. MELO's performance is improved with one iteration.

the task adaptation process and decreases the number of necessary inner-loop optimization steps. As a result, MELO guides the recommender network to reach the optimal point faster.

On the other hand, MAML needs more updates than MELO to achieve the best performance. Figure 3 shows that the RMSE and MAE values gradually decrease in proportion to the number of inner-loop updates, which requires more computation for optimization. The MAML's original paper also demonstrates that the performance improves as the number of inner-loop updates increases [6]. Furthermore, the RMSE and MAE values of MAML increase after three iterations in this experiment, which implies that it needs more computation cost to avoid overfitting and find an optimal result.

The results show that MELO is more computationally efficient than the existing MAML methodology. This fast-adaptation ability allows MELO to overcome a weakness of the MAML algorithm and make MELO extensible to real-world applications.

5.6 Ablation Study (RQ5)

We perform an ablation study over the critical components of MELO to investigate each contribution, including the sequential recommender (SR), the meta-learner (ML), and the adaptive loss (AL). Table 6 shows the results of MELO and its variants. We use BERT4Rec as a sequential recommender and conduct experiments on the Grocery dataset, which has the most imbalanced rating distribution. Hyperparameters of each variant are selected at their optimal settings.

(1) ML and AL: We remove transformer layers from BERT4Rec and leave the output layer only. This result verifies that modeling sequential information is valuable for improving the cold-start recommendation performance.

² The predicted rating distribution of the sub-sequence Y^s_i

³ The original loss value computed by the sequential recommender network

Table 6: Ablation study on the Grocery dataset

#	Architecture	RMSE	MAE	Imp	prov.
(1)	ML + AL	1.0583	0.7235	-6.21%	-8.67%
(2)	SR + AL	1.0814	0.7967	-8.22%	-17.06%
(3)	SR + ML	1.0501	0.6803	-5.49%	-2.87%
(4)	SR + ML + AL (Ours)	0.9925	0.6608	-	-

- (2) SR and AL: The result shows the advantage of the bi-level optimization from the meta-learning algorithm. It demonstrates the importance of inner-loop optimization and utilizing meta-knowledge for a personalized recommendation.
- (3) SR and ML: This variant is the MAML-only integration without the benefit of adaptive loss. The MAML algorithm struggles to capture each user's state and improve the rating prediction performance.
- (4) SR, ML, and AL: MELO, in which all components are combined, shows the best performance. The sequential recommender models a user's preferences, and the MAML algorithm identifies the optimal point of each user-specific learning with the support of the adaptive weights.

5.7 Case Study (RQ6)

In this section, we conduct a user case study to see how MELO provides a personalized recommendation experience to individual users in an imbalanced environment. First, we choose users who represent generous, fair, and grumpy preferences in the Grocery dataset, which has the most imbalanced rating distribution. A generous user has a rating score of 1 (5%), 2 (4%), 3 (4%), 4 (15%), and 5 (72%) proportion. A fair user has a rating score of 1 (28%), 2 (11%), 3 (18%), 4 (12%), and 5 (31%) proportion. A grumpy user has a rating score of 1 (58%), 2 (17%), 3 (10%), 4 (7%), and 5 (8%) proportion. We then visualize the distribution of predicted ratings to compare how well the baseline methods consider rare ratings with few records.

Figure 4 shows the case study results. Basics fail to capture the preference and the degree of imbalance information from the user sequence. As a result, they bias their prediction towards the score with the highest records. MAML displays better personalization performance but slightly lower adaptation ability for imbalanced ratings. MELO shows a similar predictive average to MAML but offers a broader range of predictions up to ratings with few records. For example, MAML fails to predict items rated as a score of 1 by the generous user, but MELO predicts better.

5.8 Discussion

This paper is the first work to address the user cold-start problem from the point of imbalanced user feedback in sequential recommender systems. While our approach presents a practical solution, there is room for future work. First, different adaptive strategies may be more appropriate in different recommender algorithms beyond sequential recommender systems and thus merit further exploration. Second, the online recommender update strategy based on the proposed sequential recommender and task state recurrent

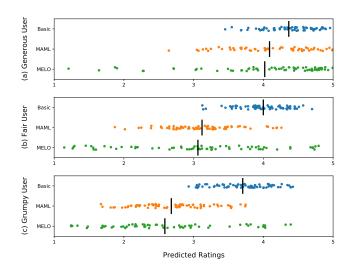


Figure 4: The predicted rating values for the representative user types: (a) generous, (b) fair, and (c) grumpy. The baseline methods predict a rating of time step t+1 by taking the sequence up to time step t at each inference. The black bar represents the arithmetic mean of predicted values.

encoder structure can increase the flexibility of learning users' upto-date interests.

6 CONCLUSION

The imbalance rating of cold-start users is a realistic and challenging problem in sequential recommenders and meta-learning contexts. In this work, we propose MELO, which effectively captures the imbalanced rating distribution of cold-start users for a personalized recommendation. Our extensive experiments on real-world datasets show that MELO outperforms the original MAML algorithm. This result underlines the importance of learning the adaptive weighted loss for each task compared to the rule-based scaling strategy. Furthermore, MELO has model-agnostic architecture and can easily integrate existing state-of-the-art sequential recommender systems to improve performance. The task state recurrent encoder receives the rating information sequentially and refines them to an informative representation, namely adaptive weights. That way, we correct the original loss by learning the adaptive weighting strategy and improve fast adaptation to each cold-start user. We believe that our study for the cold-start recommendation with imbalanced user feedback will be a momentous milestone for real-world applications.

Potential Societal Impact. Our model can be misused because a recommendation system handles privacy data. Service providers may collect user-sensitive data and store excessive amounts of information without the user's explicit consent. Therefore, we need explicit guidelines to mitigate this risk. A system administrator must go through the approval process to regulate data use and ask for only the minimum amount of anonymized information.

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