

LoRec: Large Language Model for Robust Sequential Recommendation against Poisoning Attacks

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ABSTRACT

Sequential recommender systems stand out for their ability to capture users' dynamic interests and the patterns of item-to-item transitions. However, the inherent openness of sequential recommender systems renders them vulnerable to poisoning attacks, where fraudulent users are injected into the training data to manipulate learned patterns. Traditional defense strategies predominantly depend on predefined assumptions or rules extracted from specific known attacks, limiting their generalizability to unknown attack types. To solve the above problems, considering the rich open-world knowledge encapsulated in Large Language Models (LLMs), our research initially focuses on the capabilities of LLMs in the detection of unknown fraudulent activities within recommender systems, a strategy we denote as **LLM4Dec**. Empirical evaluations demonstrate the substantial capability of LLMs in identifying unknown fraudsters, leveraging their expansive, open-world knowledge.

Building upon this, we propose the integration of LLMs into defense strategies to extend their effectiveness beyond the confines of known attacks. We propose **LoRec**, an advanced framework that employs LLM-Enhanced Calibration to strengthen the robustness of sequential Recommender systems against poisoning attacks. LoRec integrates an LLM-enhanced CalibraTor (LCT) that refines the training process of sequential recommender systems

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with knowledge derived from LLMs, applying a user-wise reweighting to diminish the impact of fraudsters injected by attacks. By incorporating LLMs' open-world knowledge, the LCT effectively converts the limited, specific priors or rules into a more general pattern of fraudsters, offering improved defenses against poisoning attacks. Our comprehensive experiments validate that LoRec, as a general framework, significantly strengthens the robustness of sequential recommender systems.

CCS CONCEPTS

- Information systems → Recommender systems;
- Security and privacy → Social network security and privacy.

KEYWORDS

Robust Sequential Recommendation, Large Language Model, Poisoning Attack

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1 INTRODUCTION

Sequential recommender systems are increasingly popular for personalized recommendations by capturing the dynamic interests of users and the evolving transition patterns of items [14, 24, 43]. However, the inherent openness of these recommender systems allows attackers to effortlessly inject fraudulent users to manipulate the learned item transition patterns, thus fulfilling objectives such as promoting target items, also known as poisoning attacks [12, 26]. Such manipulations can drastically skew the distribution of target

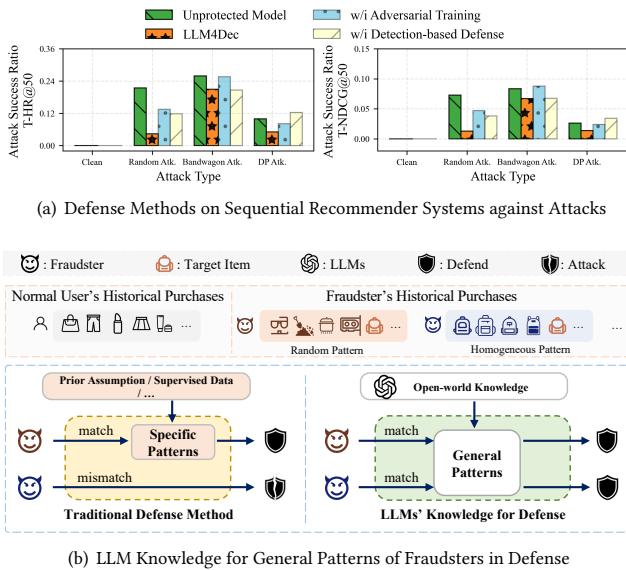


Figure 1: (a) Sequential recommender systems show vulnerability to attacks despite various defense strategies. (b) Utilizing LLMs’ open-world knowledge to enhance defense by generalizing from specific to general patterns.

item exposure within recommendations, damaging user experience and hindering the long-term development of recommender systems [39].

Defensive strategies against poisoning attacks within recommender systems typically fall into two main approaches, i.e., constructing robust models through (1) adversarial training [9, 18, 31, 35, 37], or (2) detecting and eliminating injected fraudulent users [4, 19, 34, 38, 40]. Adversarial training typically follows a “min-max” paradigm, which finds attacks that maximally damage recommendation performance and then trains the optimal model to minimize the influence of such attacks. However, this “min-max” paradigm remains a significant gap with real-world attacks, such as target item promotion [26], failing to show satisfiable defensibility. As shown in Figure 1(a), adversarial training is less effective against Bandwagon attacks [20] and DP attacks [12], which are two common target item promotion attacks.

Unlike adversarial training, detection-based methods scan the entire dataset to identify potential fraudsters according to human priors or parts of known fraudster patterns. Subsequent steps include either the removal of these identified users (hard detection) [34, 38] or diminishing their impact during training by weight adjustment (soft detection) [40]. Unfortunately, the performance of these methods is limited by their specific knowledge from heuristic priors or supervised fraudsters [4, 34, 40]. As shown in Figure 1(a), detection-based methods utilizing Bandwagon attacks as supervised data exhibit enhanced defense against such attacks, but fail to defend against DP attacks which deviate from the known supervised fraudsters. In practical scenarios, as attacks evolve, the ability of defense methods to adapt to unknown attacks is crucial. However, these methods can only mitigate impacts aligning with their specific knowledge and lack broader generalization to unknown attacks.

Recently, Large Language Models (LLMs) have achieved significant advancements across a multitude of fields, showing extraordinary capabilities in diverse applications [13, 16]. Researchers further demonstrate LLMs’ ability to encapsulate expansive open-world knowledge, which can aid various tasks in achieving improved generalizability [6, 11]. Our study commences by exploring the effectiveness of LLMs in identifying unknown fraudulent entities within recommender systems, utilizing a subset of known supervised fraudsters, namely **LLM4Dec**. Comprehensive experimental results reveal the formidable generalizability of LLMs in recognizing various types of attacks, including those previously unknown, as depicted in Figure 1(a).

Progressing from this foundation, our research addresses the limitations in the generalizability of existing defense strategies against unfamiliar attack types. This issue is illustrated in the left section of Figure 1(b). Our work investigates leveraging the open-world knowledge of LLMs to enhance defense methods. By utilizing LLMs, we aim to move beyond the specific attack patterns learned from predetermined assumptions or supervised data towards a broader understanding of fraudsters for developing robust sequential recommender systems, as shown in the right section of Figure 1(b).

we present **LoRec**, an innovative framework that leverages an LLM-Enhanced CalibraTor (LCT) to bolster the robustness of sequential Recommender systems against poisoning attacks. The LCT utilizes LLM-derived knowledge to aid in user weight calibration during the training phase of the recommender, thus mitigating the influence of fraudsters. Specifically, the LCT utilizes two types of knowledge: (1) specific knowledge that underscores the detailed differences between known fraudsters and genuine users within the recommender system, and (2) LLMs’ general knowledge regarding the fraudulence potential of given user profiles. By combining current model feedback (as specific knowledge) with LLMs’ general knowledge, the LCT gains both a zoomed-in view and a broad perspective for recognizing fraudsters in the current recommender system. As both the LCT and the sequential recommender system undergo ongoing optimization, the LCT continuously calibrates the training loss of the model via user-wise reweighing. This ensures a gradual reduction in the impact of fraudsters, preserving accurate and robust recommendations.

The pivotal contributions of our work are as follows:

- We pioneer the exploration of LLMs’ knowledge of fraudsters within the context of recommender systems, revealing how LLMs’ open-world knowledge can aid defense methods in generalizing across different types of attacks. In this vein, we propose a simple method, LLM4Dec, which leverages LLMs for the effective detection of fraudulent activities in such systems.
- We lead the initiative of incorporating LLMs into the robustness of sequential recommender systems, introducing LoRec as an innovative and general framework that employs LLM-enhanced Calibration for robust sequential recommendations.
- Our extensive experiments confirm the efficacy of the LoRec framework in withstanding diverse types of attacks and its adaptability across multiple backbone recommendation architectures.

2 RELATED WORK

This section briefly reviews the research on sequential recommender systems and robust recommender systems.

2.1 Sequential Recommender System

Early sequential recommender systems primarily rely on the Markov Chain framework to model user interactions [7, 8]. As neural network technologies advance, a shift occurs toward architectures like Recurrent Neural Networks [1, 10] and Convolutional Neural Networks [25] for capturing complex user interactions and item transition patterns. The introduction of sophisticated neural network architectures, particularly the Transformer [28], further enhances the capability of effectively capturing the nuances of dynamic user preferences. Notable works in this area include SASRec [14] and Bert4Rec [24], which leverage these advanced techniques for improved performance. More recently, researchers are exploring novel paradigms for modeling user interests, such as MLPs [41, 43], pushing the boundaries of the field. Additionally, significant efforts are made to integrate self-supervised learning into the training of sequential recommender systems, aiming to enhance recommendation performance [2, 33, 42]. Despite these advancements, the susceptibility of these models to malicious attacks remains a concern, highlighting a significant challenge [39].

2.2 Robust Recommender System

Mainstream strategies for enhancing the robustness of recommender systems against poisoning attacks broadly fall into two categories [39], the development of robust systems via (1) adversarial training [9, 18, 31, 35, 37], or (2) the removal of malicious data via detection techniques [4, 19, 34, 38, 40].

Adversarial training, under the framework of Adversarial Personalized Ranking (APR) [9], incorporates small adversarial perturbations at the parameter level during training [9, 18, 35]. This process employs a “min-max” optimization strategy, aiming to minimize recommendation loss while maximizing the impact of adversarial perturbations. This approach is predicated on the assumption that attackers aim to degrade overall recommendation performance [9, 31]. However, real-world attacks often have varied objectives, like the promotion of specific items [12, 26]. Such attacks usually do not directly undermine recommendation performance, leading to a significant discrepancy with the “min-max” paradigm. Consequently, this diminishes the defensibility of adversarial training.

Detection techniques directly identify and remove potential fraudsters before training [4, 19, 34, 38], or detect suspicious behaviors during training and softly discount their influence [40]. These detection mechanisms often incorporate specific assumptions [4, 40], or rely on supervised attack data [34, 38, 40]. For example, GraphRfi [40] assumes the unpredictability of fraudsters’ behaviors, filtering them out by contrasting predictions with actual user behaviors. Additionally, RAdabst [34] creates fraudulent data based on heuristic-based attacks [15, 20] to train its detection model. These assumptions or reliance can impede the ability of detection methods to adapt to changing attack patterns. For example, DP attacks [12], which are optimization-based, employ poisoned model predictions to create fraudulent behaviors. This challenges

GraphRfi’s assumption of unpredictability [40] and diverges from the supervised data used in RAdabst [34].

In real-world scenarios, as attacks evolve, the ability of defense methods to generalize to unknown attacks is vital. However, there is still a shortage of effective defense strategies that can generalize across various types of unknown attacks.

3 PRELIMINARY

This section mathematically formulates the task of sequential recommendation. We define the set of users as \mathcal{U} and the set of items as \mathcal{V} . Each user $u \in \mathcal{U}$ is linked with a historical interaction sequence $s_u = [v_1, v_2, \dots, v_{|s_u|}]$, wherein $v_t \in \mathcal{V}$ denotes an item interacted with user u , and $|s_u|$ denotes sequence length. The objective of sequential recommendation is to predict the next item that user u will interact with. This predictive task can be formulated as:

$$v_{|s_u|+1} = \arg \max_{v \in \mathcal{V}} \mathbb{P}(v|s_u), \quad (1)$$

where $\mathbb{P}(v|s_u)$ is the conditional probability of item v being the next item following the historical interaction sequence s_u .

4 LLM4DEC

LLMs incorporate vast open-world knowledge into their parameters, which can provide a more general understanding of identifying fraudsters. We investigate LLMs’ knowledge in fraudster detection. Firstly, we transform user interaction data into prompts to effectively query the LLMs’ knowledge about “whether the given user is a fraudster”.

In more detail, we structure the recommendation context and the user’s interaction sequence as:

*“In <recommendation scenario>,
a user’s interaction sequence is as follows:
Item 1 Features;
Item 2 Features;
...;
Item N Features.”*

where “<recommendation scenario>” specifies the recommendation context, for example, news recommendation. The term “**Features**” is the item’s side information, such as title and category. We then pose an instruction to the LLMs:

“Please assess the likelihood of this user being a fraudster.”

Let prompt_u denote the combination of the structured recommendation context, user’s interaction sequence, and the instruction message of user u , as depicted in the bottom section of Figure 2(a).

We utilize a two-layer perceptron, denoted as d , to compute the probability p_u that a user u is fraudulent:

$$p_u = d(\text{LLM}(\text{prompt}_u)), \quad (2)$$

where p_u represents the probability of user u being a fraudster. This probability p_u can serve as the training weight w_u for user u (referred to as “soft detection”), or it can be used to exclude users with high p_u values (“hard detection”) during the training of downstream recommender systems.

For fine-tuning purposes, we construct a supervised dataset of known fraudulent users, \mathcal{U}_{atk} , ensuring that $\mathcal{U}_{\text{atk}} \cap \mathcal{U} = \emptyset$. Users in \mathcal{U}_{atk} are assigned a label of 1. Ideally, we would also have a verified set of genuine users labeled as 0. However, due to practical

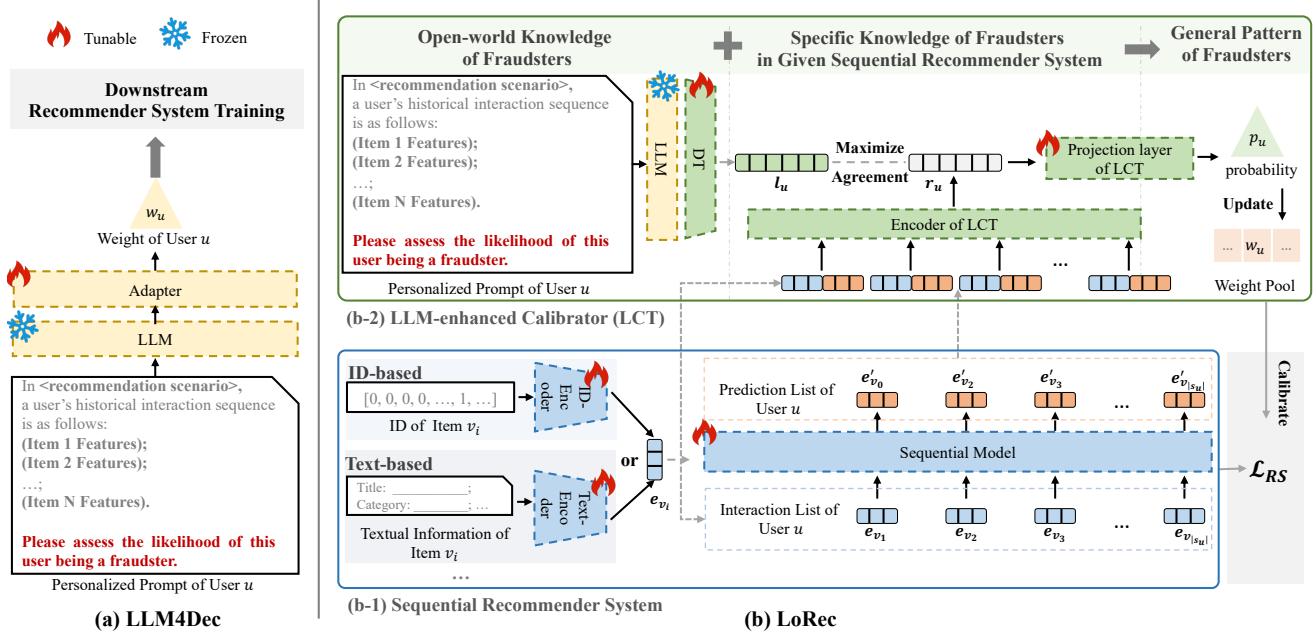


Figure 2: Overview (a) **LLM4Dec** leverages the open-world knowledge of LLMs via Supervised Fine-Tuning to detect fraudsters in recommender systems. (b) **LoRec** consists of two main elements: (b-1) Sequential Recommender System with ID-based/Text-based item encoding; (b-2) LLM-enhanced Calibrator utilizes both open-world knowledge from LLMs and specific knowledge within the sequential recommender system to calibrate user weights, enhancing its robustness against poisoning attacks.

constraints, we only have access to the observed user set \mathcal{U} , which may contain undetected fraudulent users. Consequently, users in \mathcal{U} are labeled as 0 for training purposes. This approach helps in approximating the likelihood of users being fraudsters, as defined by the following loss function:

$$\mathcal{L}_F = -\frac{1}{|\mathcal{U}_{atk}|} \sum_{u \in \mathcal{U}_{atk}} \log(p_u) - \frac{1}{|\mathcal{U}|} \sum_{u \in \mathcal{U}} \log(1 - p_u). \quad (3)$$

Given the possibility that the user set \mathcal{U} may include both genuine users and potential fraudsters (injected by attackers but we do not know), we incorporate an Entropy Regularization term for users in \mathcal{U} . This term is designed to prevent extreme predictions by the LLM4Dec:

$$\mathcal{L}_{ER} = \frac{1}{|\mathcal{U}|} \sum_{u \in \mathcal{U}} (\log(p_u) + \log(1 - p_u)). \quad (4)$$

Therefore, the final loss function for the LLM4DEC is defined as:

$$\mathcal{L}_{LLM4DEC} = \mathcal{L}_F + \lambda \mathcal{L}_{ER}, \quad (5)$$

where λ is a tunable hyperparameter.

5 LOREC

While the open-world knowledge of LLMs contributes to the generalization of defense methods, exclusive reliance on fine-tuning methods such as **LLM4Dec** might lead to overlooking some fraudsters. Consequently, integrating more detailed perspectives is imperative to enhance the robustness of recommender systems. In this context, we introduce **LoRec**, an innovative framework that employs LLM-enhanced Calibration. This framework is specifically

tailored to enhance the robustness of sequential recommender systems, addressing the limitations of previous methodologies.

5.1 Overview of LoRec

Due to the openness of sequential recommender systems, attackers can inject fraudulent users into their training data. This manipulation disrupts the item transition patterns learned by these recommender systems, maliciously promoting target items. To effectively counter these malicious activities, our primary goal is to selectively reduce the influence of users identified as potential fraudsters, ensuring that the recommender systems remain robust and unaffected by such manipulations.

A key component of this strategy is accurately differentiating between genuine users and fraudsters, especially in cases of previously unseen attacks. Consequently, we explore integrating general knowledge from LLMs about the fraudulent potential of user historical interactions into specific knowledge highlighting the detailed differences between genuine users and known fraudsters in the recommender system, enhancing generalizability to unknown attacks.

Building on this foundation, we introduce LoRec, a general and adaptable framework suitable for a variety of sequential recommender systems. LoRec comprises two main components: a backbone sequential recommendation model and an LLM-enhanced Calibrator (LCT), as illustrated in Figure 2.

Sequential Recommender System. This component can be any existing sequential recommender system. It transforms users'

historical interaction sequences into low-dimensional representations. These representations are utilized for predicting subsequent items with which users will interact, as depicted in Figure 2(a).

LLM-enhanced CalibraTor (LCT). The LCT, a novel component of LoRec, calibrates user weights by incorporating both specific knowledge within the current recommendation model and the open-world knowledge of LLMs. By combining these two types of knowledge, the LCT learns the general patterns of fraudsters. The LCT then employs these patterns to calibrate the weights assigned to each user during the training of the sequential recommender system, significantly enhancing the robustness against poisoning attacks, as shown in Figure 2(b).

5.2 Sequential Recommender System

As recommender systems evolve, their models increasingly incorporate not only user interaction behaviors but also diverse item-related side information, including texts [11, 36], images [22], and other relevant data [5]. Typically, for each item in the set \mathcal{V} , we utilize modality-specific encoders, e.g., ID-based encoders or Text-based encoders, to transform this side information into embeddings $\mathbf{e}_v \in \mathbb{R}^d$. This process is illustrated in the left section of Figure 2(a). The historical interaction sequence $s_u = [v_1, v_2, \dots, v_{|s_u|}]$ of user u can be represented at embedding-level as:

$$\mathbf{E}_u = [\mathbf{e}_{v_1}, \mathbf{e}_{v_2}, \dots, \mathbf{e}_{v_{|s_u|}}]. \quad (6)$$

The encoded sequence \mathbf{E}_u serves as the input for the sequential model g within any existing sequential recommender systems, which then generates the prediction embedding sequence $\mathbf{E}'_u = [\mathbf{e}'_{v_1}, \mathbf{e}'_{v_2}, \dots, \mathbf{e}'_{v_{|s_u|}}]$ for user u , where each $\mathbf{e}'_{v_i} \in \mathbb{R}^d$ is defined as:

$$\mathbf{e}'_{v_i} = g(\mathbf{E}_u, 1:i), \quad i = 1, 2, \dots, |s_u|. \quad (7)$$

To forecast the likelihood of subsequent items in the sequence, we leverage both the item and prediction embeddings. The probability of item v_j being the next in the sequence, given the user's historical interactions up to time i , is calculated as follows:

$$\mathbb{P}(v_{i+1} = v_j | s_u, 1:i) = \sigma(\mathbf{e}_{v_j}^\top \mathbf{e}'_{v_i}), \quad (8)$$

where $\sigma(\cdot)$ is the sigmoid function.

5.3 LLM-enhanced Calibrator

To effectively and accurately identify fraudsters in \mathcal{U} , the LCT predominantly leverages two knowledge types: specific knowledge from the current sequential recommender system regarding known fraudsters, and open-world knowledge derived from LLMs about whether a user appears fraudulent. The specific knowledge underscores the detailed differences between genuine users and known fraudsters within the current sequential recommender system. Meanwhile, the open-world knowledge provides the LCT with a universal understanding, enhancing its ability to generalize across different fraudster types. These comprehensive insights aid LCT in better identifying and diminishing the impact of users who are potentially harmful. By utilizing these two types of knowledge, the LCT gains both a zoomed-in view and a wide lens for recognizing the fraudsters in the current sequential recommender system.

5.3.1 Specific Knowledge Modeling. Specific knowledge refers to the distinctions between genuine users and known fraudsters within the current sequential recommender system. This knowledge offers detailed insights crucial for identifying fraudsters. Considering the behavioral differences between genuine users and fraudsters, we leverage feedback from the current sequential recommender system to model the specific knowledge. This involves concatenating each item's embedding \mathbf{e}_v (the feedback from the modality-specific encoder) with its predictive counterpart \mathbf{e}'_v (the feedback from the sequential model), resulting in a composite embedding $\mathbf{k}_v \in \mathbb{R}^{2d}$ for each item in the historical interaction sequence as:

$$\mathbf{k}_{v_i} = \text{concat}(\mathbf{e}_{v_i}, \mathbf{e}'_{v_i}), \quad v_i \in s_u. \quad (9)$$

Then, a learnable embedding $\mathbf{k}_0 \in \mathbb{R}^{2d}$ is used to summarize the features in $\mathbf{K}_u = [\mathbf{k}_{v_1}, \mathbf{k}_{v_2}, \dots, \mathbf{k}_{v_{|s_u|}}]$ through self-attention, producing $\mathbf{r}_u \in \mathbb{R}^{2d}$ as:

$$\mathbf{r}_u = \text{selfAtt}([\mathbf{k}_0, \mathbf{K}_u]), \quad (10)$$

where $\text{selfAtt}(\cdot)$ is the self-attention mechanism with position embeddings as employed in [28], and \mathbf{r}_u is the output corresponding to \mathbf{k}_0 . Then, a two-layer perceptron, i.e., the projection layer h , is employed to map \mathbf{r}_u onto $p_u \in [0, 1]$, which reflects the likelihood of "user u being a fraudster":

$$p_u = h(\mathbf{r}_u). \quad (11)$$

5.3.2 Open-world Knowledge Integration. Following the methodology outlined in Section 4, we generate prompt_u for each user. The output of the LLM for these prompts is transformed into a low-dimensional embedding, as shown in the following equation:

$$\mathbf{l}_u = \text{DT}(\text{LLM}(\text{prompt}_u)), \quad (12)$$

where DT denotes a Dimension Transformation (DT) block, used for transforming the dimension of the embedding. The obtained embedding $\mathbf{l}_u \in \mathbb{R}^{2d}$ contains the LLMs' open-world knowledge of whether user u exhibits characteristics of fraudsters.

Next, we aim to maximize the agreement between the representations \mathbf{l}_u and \mathbf{r}_u to integrate the open-world knowledge:

$$\max \text{sim}(\mathbf{l}_u, \mathbf{r}_u), \quad \forall u \in \mathcal{U}, \quad (13)$$

where $\text{sim}(\cdot)$ is the cosine similarity function. Such agreement maximization can further help the representation \mathbf{r}_u considering fraudster characteristics from both specific knowledge within the current sequential recommender system and the LLMs' open-world knowledge, thereby better reflecting the likelihood p_u of the user u being a fraudster.

LLM-enhanced Loss. In the final step, we integrate the open-world knowledge into \mathbf{r}_u to extend the specific knowledge of known fraudsters to a more general pattern within the current sequential recommender system. This integration is achieved by incorporating these agreements into the LCT's training loss function:

$$\mathcal{L}_{\text{LLM}} = -\frac{1}{|\mathcal{U} \cup \mathcal{U}_{\text{atk}}|} \sum_{u \in \mathcal{U} \cup \mathcal{U}_{\text{atk}}} \text{sim}(\mathbf{l}_u, \mathbf{r}_u). \quad (14)$$

Consequently, the final loss function for the LCT is formulated as follows:

$$\mathcal{L}_{\text{LCT}} = \mathcal{L}_{\text{F}} + \lambda_1 \mathcal{L}_{\text{ER}} + \lambda_2 \mathcal{L}_{\text{LLM}}, \quad (15)$$

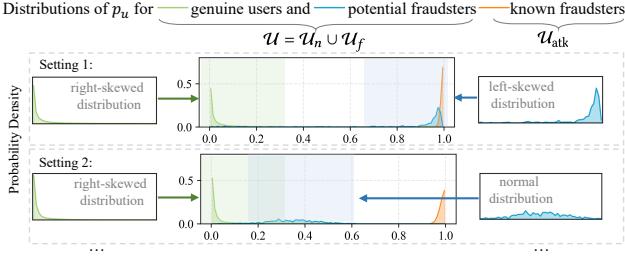


Figure 3: For LCT with different settings (hyperparameters, training epochs, or attack types), the learned probability p_u for genuine users \mathcal{U}_n and potential fraudsters \mathcal{U}_f follow different distributions.

where \mathcal{L}_F and \mathcal{L}_{ER} are as defined in Equation 3 and Equation 4, respectively, and λ_1 and λ_2 are hyperparameters.

5.4 Calibration for Robust Recommendation

As mentioned above, in practical scenarios, the existence of fraudsters within the training user set \mathcal{U} is typically unknown. The user set \mathcal{U} consists of both genuine users \mathcal{U}_n and potential fraudsters \mathcal{U}_f . However, all users, including those potentially fraudulent, are initially assigned a label of 0, as delineated in Equation 3. In such situations, it is challenging to guarantee a distinct demarcation between the p_u values of genuine users and those of potential fraudsters, as shown in the bottom setting of Figure 3. To address this, we implement an adaptive threshold for more effectively identifying potential fraudsters and introduce an iterative weight compensation mechanism to minimize the misidentification risk of users.

Observation. A well-trained classifier often displays a skewed distribution in its logit outputs, a phenomenon sometimes referred to as over-confidence [30]. We leverage this characteristic for more effective fraudster identification. We observe that, for users in \mathcal{U}_n , the logits post-LCT projection layer exhibit a pronounced skew towards $p_u = 0$, i.e., a right-skewed distribution¹. For \mathcal{U}_f , the logit distribution can vary in different settings (hyperparameters, training epochs, attacks, etc.), as shown in Figure 3.

Adaptive Threshold. Without loss of generality, assuming a well-trained LCT, p_u for \mathcal{U}_n follow a right-skewed distribution with mean μ_n , while those for \mathcal{U}_f approximate either a normal distribution or a left-skewed distribution with mean μ_f , where $\mu_n < \mu_f$. Let γ represent the ratio $\frac{|\mathcal{U}_f|}{|\mathcal{U}_n|}$, satisfying $0 \leq \gamma < 1$. The mean μ_o of the overall p_u in \mathcal{U} is:

$$\mu_o = \frac{1}{|\mathcal{U}|} \sum_{u \in \mathcal{U}} p_u = \frac{(\mu_n + \gamma\mu_f)}{1 + \gamma}, \quad (16)$$

where $\mu_n < \mu_o < \mu_f$. Simply, we can employ μ_o as the adaptive threshold to identify potential fraudsters.

Iterative Weight Compensation. However, directly applying μ_o as the adaptive threshold introduces two challenges: (1) some genuine users with $p_u > \mu_o$ may be misclassified, while (2) some potential fraudsters remain unidentified. To mitigate this, we introduce an iterative weight compensation mechanism. We establish a weight pool tracking per-user weight coefficients $\xi_u, \forall u \in \mathcal{U}$,

¹A right-skewed distribution is characterized by a long right tail, where the mean exceeds the median [29].

initially set to $\hat{\xi}$. Upon reaching certain training epochs with the LCT, ξ_u is updated as:

$$\xi_u(t+1) = \begin{cases} \xi_u(t) - 1, & \text{if } p_u > \mu_o, \\ \xi_u(t) + \frac{\sum_{u \in \mathcal{U}} \mathbb{I}(p_u > \mu_o)}{\sum_{u \in \mathcal{U}} \mathbb{I}(p_u \leq \mu_o)}, & \text{if } p_u \leq \mu_o, \end{cases} \quad (17)$$

where $\mathbb{I}(\cdot)$ returns 1 when the condition is true. The notation $\xi_u(t)$ represents the value of ξ_u after t updates, with $\xi_u(0) = \hat{\xi}$.

PROPOSITION 5.1. Consider i.i.d. samples n_0, n_1, \dots, n_N drawn from a right-skewed distribution with mean μ_n , and z_0, z_1, \dots, z_Z drawn from either a normal distribution or a left-skewed distribution with mean μ_f . Let ξ_{n_i} and ξ_{z_j} represent the weight coefficients for n_i and z_j , respectively. We denote $\bar{\xi}_n = \frac{1}{N} \sum_{i=0}^N \xi_{n_i}$, and $\bar{\xi}_z = \frac{1}{Z} \sum_{j=0}^Z \xi_{z_j}$. Given μ_o satisfying $\mu_n < \mu_o < \mu_f$, and updating these coefficients according to Equation 17, it can be shown that $\mathbb{E}[\bar{\xi}_n(t) - \bar{\xi}_n(t+1)] > 0$ and $\mathbb{E}[\bar{\xi}_z(t) - \bar{\xi}_z(t+1)] < 0$.

PROOF. Let α denote the probability $\mathbb{P}_n(n > \mu_o)$ and β denote the probability $\mathbb{P}_z(z > \mu_o)$. Let γ represent the ratio $\frac{\gamma}{N}$. Define $F_n(\cdot)$ as the Cumulative Distribution Function (CDF) of the right-skewed distribution $\mathbb{P}_n(n)$, characterized by mean μ_n and median m_n , and $F_z(\cdot)$ as the CDF of either the normal or left-skewed distribution $\mathbb{P}_z(z)$, with mean μ_f and median m_f . It follows that $F_n(\mu_n) > F_n(m_n) = 0.5$, and $F_z(\mu_f) \leq F_z(m_f) = 0.5$. With $\mu_n < \mu_o < \mu_f$, we derive:

$$\begin{aligned} \alpha &= 1 - F_n(\mu_o) < 1 - F_n(\mu_n) < 0.5, \\ \beta &= 1 - F_z(\mu_o) > 1 - F_z(\mu_f) \geq 0.5. \end{aligned} \quad (18)$$

Therefore, $\alpha < \beta$. The change between $\bar{\xi}_z(t)$ and $\bar{\xi}_z(t+1)$ at each update is given by

$$\begin{aligned} \mathbb{E}[\Delta \bar{\xi}_z] &= \left[\frac{\alpha + \gamma\beta}{1 + \gamma - (\alpha + \gamma\beta)} \cdot \gamma N(1 - \beta) - \gamma N\beta \right] \cdot (\gamma N)^{-1} \\ &= \frac{\alpha - \beta}{1 + \gamma - (\alpha + \gamma\beta)}. \end{aligned} \quad (19)$$

Since $\alpha < \beta$ and $\alpha, \beta \in (0, 1)$, it follows that $\mathbb{E}[\Delta \bar{\xi}_z] < 0$. Similarly, $\mathbb{E}[\Delta \bar{\xi}_n] > 0$ for ξ_n . Thus, Proposition 5.1 is proved. \square

Continuous training of the sequential recommender system and consequent changes in LCT inputs for each $u \in \mathcal{U}$ lead to **evolving and rearranging** p_u distributions from LCT outputs. Based on Proposition 5.1, this ensures that the weight coefficients for fraudsters decrease with each update.

Training Calibration. We then calculate user weights as:

$$w_u = q \cdot \sigma(\xi_u), \quad (20)$$

where $q = \sigma(\hat{\xi})^{-1}$ so that all the weights used in the initial state are 1.0. Finally, the loss of sequential recommender system (using SASRec [14] as an example) is:

$$\mathcal{L}_{RS} = - \sum_{u \in \mathcal{U}} w_u \sum_{i=1}^{|s_u|-1} \left[\log(\sigma(\mathbf{e}_{v_{i+1}}^\top \mathbf{e}'_{v_i})) + \sum_{j \notin s_{u,1:i+1}} \log(1 - \sigma(\mathbf{e}_{v_j}^\top \mathbf{e}'_{v_i})) \right]. \quad (21)$$

Table 1: Dataset statistics

DATASET	#Users	#Items	#Ratings	Avg.length	Sparsity
Games	61,521	33,243	541,789	8.8	99.97%
Arts	71,364	61,505	600,989	8.4	99.99%
MIND	152,909	63,608	4,186,679	27.4	99.96%

6 EXPERIMENTS

In this section, we conduct extensive experiments to answer the following research questions (**RQs**).

- **RQ1:** Whether LoRec can defend against poisoning attacks?
- **RQ2:** What does each component of LoRec bring?
- **RQ3:** Is LoRec adaptable to diverse recommendation settings and backbone models?

6.1 Experimental Setup

6.1.1 Datasets. In our evaluation of LoRec, we employ three widely recognized datasets: the Amazon review datasets (**Games** and **Arts**) [21], and the **MIND** news recommendation dataset [32]. For the Amazon datasets, all users are considered. For the MIND dataset, a subset of 200,000 users is sampled following [17]. Consistent with existing practices [14, 23], we exclude users with fewer than 5 interactions. For each user, the data split process involves (1) using the most recent action for testing, (2) the second most recent action for validation, and (3) all preceding actions (up to 50) for training [14, 17, 36]. Dataset statistics are provided in Table 1.

6.1.2 Backbone Models. We employ three backbone sequential recommender systems:

- **GRU4rec** [10] utilizes Recurrent Neural Networks [3] to model user interaction sequences in session-based recommendations.
- **SASRec** [14] employs a multi-head self-attention mechanism in Transformer [28] for sequential recommendations.
- **FMLPrec** [43] is an all-Multilayer Perceptron model with a learnable filter-enhanced block for noise reduction in embeddings for sequential recommendations.

Due to space limitations, we predominantly show results using SASRec as the backbone model in Section 6.2. Results for GRU4rec and FMLPrec are described in Section 6.4.3. Additionally, we consider both Text-based and ID-based sequential recommender systems as depicted in Figure 2(a), but mainly focus on Text-based sequential recommender systems, while ID-based results are elaborated in Section 6.4.2.

6.1.3 Baselines for Defense. We include various methods such as the adversarial training methods APR [9] and ADVTrain [37]; a detection-based method, GraphRfi [40]. We also include two denoise-based approaches, StDenoise [27, 35] and CL4Srec [33].

- **APR** [9]: Adversarial training in recommender systems that generates small parameter perturbations using Stochastic Gradient Descent (SGD) and integrates these perturbations into training.
- **ADVTrain** [37]: This adversarial training technique counters profile pollution attacks in sequential recommender systems.
- **GraphRfi** [40]: A Graph Convolutional Network and Neural Random Forest-based framework for fraudster detection during training. We adapt it in sequential recommendations.

- **StDenoise** [27, 35]: A structural denoising method that leveraging similarity between e_v and e'_v for $v \in s_u$ as evidence for noise purification, as employed in [27, 35].
- **CL4Srec** [33]: A contrastive learning framework for sequential recommender systems to resist noise. We specifically use the “Crop” data augmentation technique.

6.1.4 Attack Methods. We consider heuristic attacks, i.e., Random Attack [15] and Bandwagon Attack [20], alongside optimized-based methods, i.e., DP Attack [12] and Rev Attack [26]. These attacks are executed in a black-box scenario where the attackers lack knowledge about the victim model’s architecture and parameters.

- **Random Attack** (Heuristic Method) [15]: Interactions of fraudsters include both target items and randomly selected items.
- **Bandwagon Attack** (Heuristic Method) [20]: Interactions of fraudsters include target items and items selected based on their popularity.
- **DP Attack** (Optimization-based Method) [12]: Targeting deep learning recommender systems specifically.
- **Rev Attack** (Optimization-based Method) [26]: Framing the attack as a bi-level optimization problem solved using gradient-based techniques.

6.1.5 Evaluation Metrics. We employ standard metrics commonly used in sequential recommender systems. For recommendation performance, the primary metrics are the top- k recommendation performance metrics: Hit Ratio at k (HR@ k) and Normalized Discounted Cumulative Gain at k (NDCG@ k), as referenced in [14, 39]. To assess the success ratio of attacks, we use metrics specific to the target items’ top- k performance, denoted as T-HR@ k and T-NDCG@ k [12, 26]:

$$\text{T-HR}@k = \frac{1}{|\mathcal{T}|} \sum_{tar \in \mathcal{T}} \frac{\sum_{u \in \mathcal{U}_n - \mathcal{U}_{n,tar}} \mathbb{I}(\text{tar} \in L_{u,k})}{|\mathcal{U}_n - \mathcal{U}_{n,tar}|}, \quad (22)$$

where \mathcal{T} represents the set of target items, $\mathcal{U}_{n,tar}$ denotes the set of genuine users who interacted with target item tar , $L_{u,k}$ is the top- k recommendation list for user u , and $\mathbb{I}(\cdot)$ is an indicator function that returns 1 if the condition is true. T-NDCG@ k mirrors T-HR@ k , serving as the target item-specific version of NDCG@ k .

Additionally, in line with the robustness definition presented in [39], we consider the variance in recommendation performance before and after an attack as an indicator of robustness, termed top- k Recommendation Consistency (RC@ k):

$$\text{RC}_{\text{HR}}@k = 1 - \frac{|\text{HR}@k - \text{HR}@k_{\text{clean}}|}{\text{HR}@k_{\text{clean}}}, \quad (23)$$

where $\text{HR}@k_{\text{clean}}$ is the top- k HR on clean dataset. $\text{RC}_{\text{NDCG}}@k$ is calculated similarly for the NDCG@ k .

6.1.6 Implementation Details. In our research, we adopt **Llama2** family into LCT. For evaluating the success ratio of attacks, we set $k = 50$ [12, 26, 31]. For recommendation performance metrics, we utilize $k = 10$ [14, 43]. In implementing both defense methods and backbone models, the learning rate is selected from $\{0.1, 0.01, \dots, 1 \times 10^{-5}\}$. Similarly, weight decay is chosen from $\{0, 0.1, \dots, 1 \times 10^{-5}\}$. Backbone model architectures follow their original publications. For the APR, we select the parameter ϵ from within the range of $\{0.02, 0.03, \dots, 0.05\}$. This selection is based on the observation that values

Table 2: Robustness against target items promotion

Dataset	Model	Random Attack(%)		Bandwagon Attack(%)		DP Attack(%)		Rev Attack(%)	
		T-HR@50 ¹	T-NDCG@50	T-HR@50	T-NDCG@50	T-HR@50	T-NDCG@50	T-HR@50	T-NDCG@50
Games	Backbone	0.889 ± 0.073	0.242 ± 0.006	0.904 ± 0.138	0.232 ± 0.010	0.458 ± 0.070	0.113 ± 0.005	0.858 ± 0.154	0.235 ± 0.014
	+StDenoise	0.633 ± 0.029	0.174 ± 0.003	1.106 ± 0.150	0.288 ± 0.011	0.334 ± 0.026	0.079 ± 0.002	1.132 ± 0.136	0.310 ± 0.011
	+CL4Srec	0.748 ± 0.025	0.199 ± 0.002	1.165 ± 0.104	0.302 ± 0.009	0.529 ± 0.064	0.129 ± 0.005	1.240 ± 0.145	0.346 ± 0.012
	+APR	0.377 ± 0.047	0.162 ± 0.012	0.756 ± 0.056	0.224 ± 0.005	0.449 ± 0.069	0.118 ± 0.006	0.362 ± 0.002	0.126 ± 0.000
	+ADVTrain	0.962 ± 0.065	0.294 ± 0.008	1.170 ± 0.017	0.305 ± 0.001	0.336 ± 0.046	0.082 ± 0.003	0.713 ± 0.088	0.210 ± 0.010
	+GraphRfi	0.819 ± 0.037	0.225 ± 0.003	0.895 ± 0.075	0.231 ± 0.006	0.506 ± 0.024	0.122 ± 0.001	0.950 ± 0.137	0.267 ± 0.013
	+LLM4Dec	0.303 ± 0.009	0.078 ± 0.001	0.235 ± 0.006	0.057 ± 0.000	0.319 ± 0.008	0.077 ± 0.001	0.432 ± 0.020	0.112 ± 0.001
	+LoRec	0.068 ± 0.002	0.016 ± 0.000	0.105 ± 0.007	0.024 ± 0.000	0.103 ± 0.001	0.024 ± 0.000	0.080 ± 0.001	0.019 ± 0.000
Gain ²		+81.97% ↑	+89.89% ↑	+86.16% ↑	+89.10% ↑	+69.04% ↑	+69.61% ↑	+78.05% ↑	+84.73% ↑
Arts	Backbone	5.646 ± 1.030	1.926 ± 0.298	4.078 ± 1.168	1.109 ± 0.109	1.978 ± 0.529	0.479 ± 0.044	OOD ³	OOD
	+StDenoise	4.498 ± 0.979	1.312 ± 0.100	4.822 ± 0.327	1.340 ± 0.028	2.195 ± 0.974	0.611 ± 0.090	OOD	OOD
	+CL4Srec	4.988 ± 0.926	1.479 ± 0.119	4.517 ± 0.710	1.282 ± 0.080	1.676 ± 0.320	0.420 ± 0.024	OOD	OOD
	+APR	5.331 ± 0.696	1.467 ± 0.464	3.762 ± 0.619	1.077 ± 0.443	1.943 ± 0.128	0.917 ± 0.010	OOD	OOD
	+ADVTrain	3.520 ± 0.927	1.009 ± 0.089	4.659 ± 3.614	1.316 ± 0.370	1.886 ± 0.338	0.504 ± 0.031	OOD	OOD
	+GraphRfi	5.331 ± 0.609	1.553 ± 0.048	3.542 ± 1.544	0.957 ± 0.120	1.814 ± 0.408	0.452 ± 0.025	OOD	OOD
	+LLM4Dec	1.338 ± 0.194	0.342 ± 0.015	0.679 ± 0.021	0.176 ± 0.002	0.790 ± 0.015	0.197 ± 0.001	OOD	OOD
	+LoRec	0.576 ± 0.027	0.141 ± 0.002	0.436 ± 0.061	0.108 ± 0.004	0.440 ± 0.042	0.109 ± 0.003	OOD	OOD
Gain		+42.42% ↑	+85.89% ↑	+56.44% ↑	+88.72% ↑	+56.02% ↑	+74.08% ↑	-	-
MIND	Backbone	0.215 ± 0.015	0.073 ± 0.002	0.259 ± 0.006	0.083 ± 0.001	0.099 ± 0.002	0.026 ± 0.002	OOD	OOD
	+StDenoise	0.193 ± 0.001	0.062 ± 0.001	0.337 ± 0.028	0.111 ± 0.003	0.088 ± 0.003	0.025 ± 0.002	OOD	OOD
	+CL4SRec	0.166 ± 0.008	0.054 ± 0.001	0.259 ± 0.015	0.082 ± 0.002	0.093 ± 0.001	0.026 ± 0.000	OOD	OOD
	+APR	0.135 ± 0.020	0.047 ± 0.001	0.256 ± 0.004	0.088 ± 0.001	0.082 ± 0.002	0.024 ± 0.001	OOD	OOD
	+ADVTrain	0.141 ± 0.001	0.048 ± 0.000	0.319 ± 0.010	0.104 ± 0.001	0.127 ± 0.003	0.036 ± 0.000	OOD	OOD
	+GraphRfi	0.118 ± 0.001	0.038 ± 0.001	0.206 ± 0.003	0.067 ± 0.001	0.123 ± 0.003	0.034 ± 0.001	OOD	OOD
	+LLM4Dec	0.044 ± 0.001	0.013 ± 0.000	0.219 ± 0.003	0.068 ± 0.002	0.051 ± 0.000	0.014 ± 0.002	OOD	OOD
	+LoRec	0.005 ± 0.001	0.001 ± 0.000	0.012 ± 0.001	0.003 ± 0.001	0.004 ± 0.001	0.001 ± 0.000	OOD	OOD
Gain		+95.61% ↑	+96.28% ↑	+94.29% ↑	+95.10% ↑	+95.07% ↑	+95.92% ↑	-	-

¹ Target Item Hit Ratio (Equation 22); T-HR@50 and T-NDCG@50 of all target items on clean datasets are 0.000.² The relative percentage increase of LoRec's metrics to the best value of other baselines' metrics, i.e., $(\min(T\text{-HR}_{\text{Beslines}}) - T\text{-HR}_{\text{LoRec}}) / \min(T\text{-HR}_{\text{Beslines}})$.³ The Rev attack method could not be executed on the dataset due to memory constraints, resulting in an out-of-memory error.

of ϵ greater than 0.05 tend to negatively impact recommendation performance. The implementation of GraphRfi follows its paper. For the detection-based methods and our method, the Bandwagon Attack is provided as supervised fraudster data, denoted as \mathcal{U}_{atk} . The size of \mathcal{U}_{atk} is consistently set at 10% of $|\mathcal{U}|$. Regarding the attack methods, the attack budget is established at 1% with five target items. The hyperparameters are in alignment with those detailed in their original publications. Our implementation code is accessible via the provided link².

6.2 Performance Comparison (RQ1)

In this section, we answer **RQ1**. We focus on two key aspects: its robustness against poisoning attacks and its robustness in maintaining recommendation performance.

6.2.1 Robustness Against Poisoning Attacks. We evaluate the efficacy of LoRec in defending against poisoning attacks, focusing on the success ratio of attacks. In our experiments, we specifically target extremely unpopular items, resulting in values of T-HR@50 and T-NDCG@50 being 0.0 without any attack. **Note:** The lower the values of T-HR@50 and T-NDCG@50, the better the defensibility. Table 2 shows that denoise-based methods, such as StDenoise and CL4Srec, exhibit unstable performance against attacks, sometimes even increasing the attack success ratio, suggesting the inadequacy of simple denoising in attack defense. GraphRfi generally exhibits

better defense against attacks similar to its supervised data. However, with different attack types, such as DP attacks and Rev Attacks, GraphRfi's effectiveness significantly diminishes, potentially leading to an increased success ratio of attacks.

In contrast, LLM4Dec, depending exclusively on LLMs' open-world knowledge for detection, surpasses most baselines. This highlights the capability of LLMs' knowledge in identifying fraudsters. Furthermore, LoRec demonstrates superior performance compared to the baselines, significantly lowering the success ratio of attacks. For the three datasets, LoRec reduces the average T-HR@50 by 78.81%, 51.63%, and 94.99%, and the average T-NDCG@50 by 83.33%, 51.63%, and 95.76%, respectively, compared to the best results of the baselines. These results demonstrate the effectiveness of LoRec in defending against various known or unknown attacks.

6.2.2 Robustness in Maintaining Recommendation Performance. We evaluate LoRec's ability to preserve recommendation consistency in the face of poisoning attacks. Due to space limitations, we present results only for the MIND dataset. As shown in Table 3, LoRec surpasses or is comparable with existing defense mechanisms, achieving an average RC_{HR}@10 of 99.67% and RC_{NDCG}@10 of 99.39%.

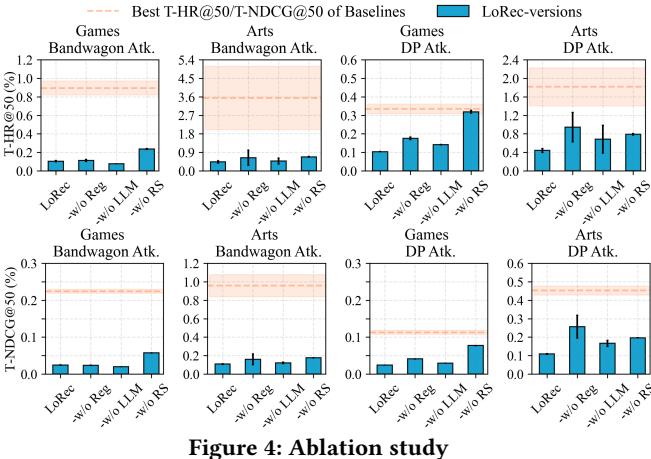
6.3 Augmentation Analysis (RQ2)

In this section, we answer **RQ2**. Our focus is on analyzing the efficacy of each component within LoRec and examining the impact of hyperparameters and the size of the LLM. Due to space limitations,

²<https://anonymous.4open.science/r/LoRec>

Table 3: Recommendation consistency

Model	Clean (%)		Random Attack (%)		Bandwagon Attack (%)		DP Attack (%)	
	RC _{HR} @10 (HR) ¹	RC _{NDCG} @10 (NDCG)	RC _{HR} @10 (HR)	RC _{NDCG} @10 (NDCG)	RC _{HR} @10 (HR)	RC _{NDCG} @10 (NDCG)	RC _{HR} @10 (HR)	RC _{NDCG} @10 (NDCG)
Backbone	- (11.289)	- (5.628)	99.46% (11.228)	99.73% (5.613)	98.52% (11.122)	98.44% (5.540)	98.64% (11.442)	98.26% (5.726)
+StDenoise	98.72% (11.144)	98.79% (5.560)	99.68% (11.253)	99.63% (5.607)	99.97% (11.286)	98.79% (5.696)	99.98% (11.287)	99.96% (5.630)
+CL4Srec	99.17% (11.383)	99.89% (5.567)	97.67% (11.026)	97.85% (5.507)	99.03% (11.179)	99.00% (5.572)	99.87% (11.304)	99.88% (5.635)
+APR	90.81% (10.252)	92.11% (5.184)	94.06% (10.618)	97.21% (5.471)	90.18% (10.180)	91.33% (5.140)	89.09% (10.057)	91.58% (5.154)
+ADVTrain	99.15% (11.193)	96.09% (5.408)	99.47% (11.229)	96.57% (5.435)	98.89% (11.163)	96.57% (5.435)	98.35% (11.475)	97.97% (5.514)
+GraphRF	99.28% (11.370)	98.60% (5.707)	98.41% (11.469)	98.53% (5.711)	99.34% (11.215)	98.97% (5.570)	98.86% (11.418)	97.73% (5.756)
+LLM4Dec	98.90% (11.165)	98.56% (5.547)	99.49% (11.231)	99.63% (5.607)	96.68% (10.914)	96.64% (5.439)	98.20% (11.086)	98.56% (5.547)
+LoRec	99.66% (11.327)	99.00% (5.684)	99.96% (11.293)	99.80% (5.639)	99.06% (11.183)	99.40% (5.594)	99.98% (11.287)	99.34% (5.665)

¹ Recommendation Consistency (Equation 23). Here, HR and NDCG are abbreviations of HR@10 and NDCG@10, respectively.**Figure 4: Ablation study**

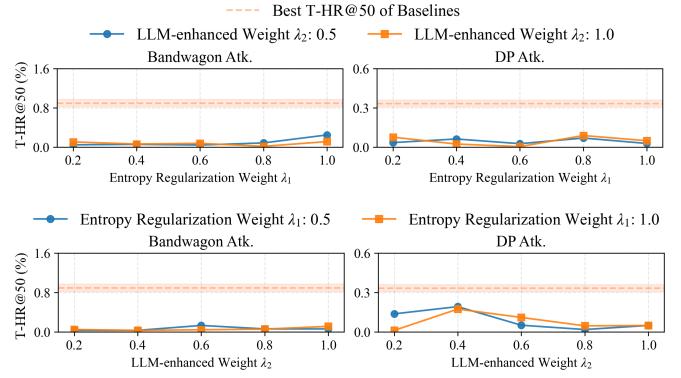
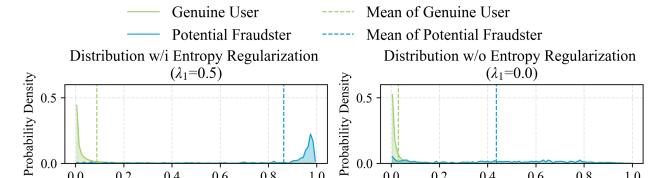
we only show the results on Games and Arts, while the MIND dataset holds consistent results.

6.3.1 Ablation Study. We first examine different variants of LoRec to evaluate the contribution of each component to its overall performance. The variants are defined as follows:

- **-w/o Reg:** This version operates without Entropy Regularization, setting $\lambda_1 = 0$ in Equation 15.
- **-w/o LLM:** This version operates without the open-world knowledge provided by LLMs, setting $\lambda_2 = 0$ in Equation 15.
- **-w/o RS:** This version operates without feedback from sequential recommender systems, rendering it equivalent to LLM4Dec.

As depicted in Figure 4, our findings reveal that each component plays a vital role in ensuring robust recommendations. All variants of LoRec outperform the best metrics achieved by the baseline models. Specifically, Entropy Regularization stabilizes the defense capability, reducing the variance of the performance. Additionally, it is observed that the LLMs' open-world knowledge has a more pronounced impact when countering the unknown DP attacks, as compared to the Bandwagon Attack which is the same type of attack in supervised data. LLMs' open-world knowledge aids LoRec in deriving a more general pattern beyond the supervised data, enhancing its effectiveness in tackling other unseen types of attacks. Lastly, feedback from the sequential recommender system emerges as a crucial element. This feedback significantly enhances LoRec's ability to accurately mitigate fraudsters' impact for achieving robust sequential recommendations.

6.3.2 Hyperparameter Analysis. We explore the effects of hyperparameters, i.e., Entropy Regularization Weight λ_1 and LLM-Enhanced

**Figure 5: Hyperparameter analysis on Entropy Regularization λ_1 and LLM-enhanced weights λ_2** **Figure 6: Influence of Entropy Regularization on distributions of genuine users and potential fraudsters**

Weight λ_2 as defined in Equation 15. We investigate the influence of varying λ_2 while holding λ_1 constant at either 0.5 or 1.0, and conversely, altering λ_1 while λ_2 remains fixed at 0.5 or 1.0. As shown in Figure 5, the results indicate that the performance remains comparatively stable despite changes in λ_1 or λ_2 .

As illustrated in the lower part of Figure 5, adjustments in λ_2 reveal that, for the Bandwagon Attack (mirroring the supervised data), a smaller λ_2 is sufficient for LoRec's effective defense. This sufficiency stems from the supervised data providing ample information for defending against similar attacks. Conversely, for the DP attacks (differing from the supervised data), a larger λ_2 enhances LoRec's performance. This improvement is attributed to the additional useful open-world knowledge, which assists the model in learning more general patterns of attacks.

Moreover, we investigate the influence of Entropy Regularization Weight λ_1 on the distributions of p_u . By preventing the model from making extreme predictions, Entropy Regularization contributes to more distinctly separating the p_u of potential fraudsters from those of genuine users, as illustrated in Figure 6.

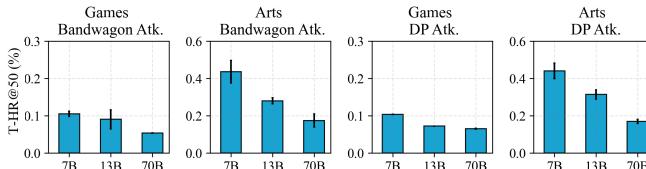


Figure 7: Performance comparison of LoRec variants utilizing Llama2 with different sizes

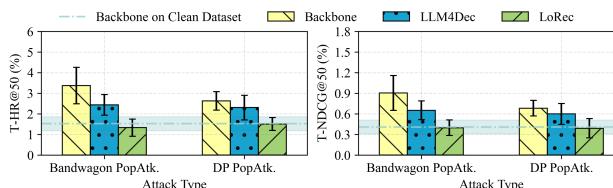


Figure 8: Robustness against the popular items promotion

6.3.3 LLMs' Size Analysis. We investigate the influence of LLMs in varying sizes on LoRec's performance. As shown in Figure 7, we find that as the size of the LLMs increases, there is a general trend towards enhanced defensibility against poisoning attacks in LoRec.

6.4 Generality of LoRec (RQ3)

We answer **RQ3** by evaluating LoRec's performance in diverse settings and across various backbone sequential recommender systems. Due to space constraints and the fact that LLM4Dec surpasses all baseline methods (refers to Table 2), we present results focusing on the Games and Arts datasets with LLM4Dec and LoRec.

6.4.1 Defensibility against Different Types of Target Item. Here, we evaluate the defensive capabilities against attacks targeting popular items, as presented in Figure 8. These findings reveal that LoRec maintains a robust defense even against attacks aimed at promoting popular items, closely aligning with the backbone model's T-HR@50 and T-NDCG@50 metrics on clean datasets.

6.4.2 Adaptation to Different Settings in Sequential Recommender Systems. We investigate the adaptability of LoRec across different configurations to assess its generalizability. In the ID-based setup of sequential recommender systems, LoRec consistently delivers the most robust outcomes, confirming its superior performance, as detailed in Table 4.

6.4.3 Generalization Across Various Recommender Systems. To ascertain LoRec's broad applicability, we evaluate its performance using different backbone sequential recommendation models. As indicated in Table 5, we employ GRU4rec [10] and FMLPrec [43] as alternative backbone sequential recommender systems. It is noted that FMLPrec itself demonstrates the strongest robustness against poisoning attacks among SASrec (the backbone model in Table 2), GRU4rec, and FMLPrec. For all these backbone models, LoRec consistently achieves the most robust results against attacks.

7 CONCLUSION

In this work, we first investigate the LLMs' knowledge of fraudster detection, proposing **LLM4Dec**. Based on the observation of LLMs' powerful generalizability, we introduce **LoRec**, a novel framework

Table 4: Robustness against target items promotion of ID-based sequential recommender system

Dataset	Model	Bandwagon Attack(%)		DP Attack(%)	
		T-HR@50	T-NDCG@50	T-HR@50	T-NDCG@50
Games	Backbone	1.517 ± 0.677	0.416 ± 0.053	0.275 ± 0.043	0.061 ± 0.002
	+LLM4Dec	0.499 ± 0.185	0.130 ± 0.014	0.237 ± 0.054	0.052 ± 0.003
	+LoRec	0.292 ± 0.166	0.080 ± 0.014	0.086 ± 0.015	0.020 ± 0.001
Arts	Backbone	7.098 ± 3.853	2.603 ± 0.240	1.708 ± 0.631	0.427 ± 0.038
	+LLM4Dec	1.261 ± 0.034	0.366 ± 0.002	1.092 ± 0.003	0.320 ± 0.000
	+LoRec	0.609 ± 0.507	0.162 ± 0.035	0.224 ± 0.016	0.051 ± 0.001

Table 5: Robustness against target items promotion of GRU4rec and FMLPrec

Dataset	Model	Bandwagon Attack(%)		DP Attack(%)	
		T-HR@50	T-NDCG@50	T-HR@50	T-NDCG@50
Games	GRU4rec	1.623 ± 0.143	0.462 ± 0.014	1.141 ± 0.460	0.310 ± 0.046
	+LLM4Dec	0.605 ± 0.168	0.249 ± 0.053	0.992 ± 0.115	0.212 ± 0.020
	+LoRec	0.229 ± 0.010	0.061 ± 0.001	0.144 ± 0.010	0.044 ± 0.002
Arts	FMLPrec	0.228 ± 0.122	0.072 ± 0.014	0.143 ± 0.002	0.036 ± 0.000
	+LLM4Dec	0.138 ± 0.011	0.029 ± 0.000	0.104 ± 0.013	0.027 ± 0.001
	+LoRec	0.038 ± 0.001	0.009 ± 0.000	0.071 ± 0.011	0.010 ± 0.001
Games	GRU4rec	7.008 ± 5.912	2.445 ± 0.982	3.573 ± 1.769	1.149 ± 0.283
	+LLM4Dec	2.135 ± 0.954	0.765 ± 0.262	1.754 ± 0.420	0.493 ± 0.045
	+LoRec	0.358 ± 0.057	0.091 ± 0.004	0.601 ± 0.204	0.177 ± 0.020
Arts	FMLPrec	0.675 ± 0.089	0.179 ± 0.006	1.471 ± 0.474	0.480 ± 0.071
	+LLM4Dec	0.108 ± 0.000	0.027 ± 0.000	0.436 ± 0.053	0.130 ± 0.005
	+LoRec	0.096 ± 0.003	0.024 ± 0.000	0.328 ± 0.016	0.098 ± 0.001

that employs LLM-enhanced Calibration to enhance the robustness of sequential recommender systems against poisoning attacks. LoRec integrates an LLM-enhanced Calibrator, integrating extensive open-world knowledge from LLMs into specific knowledge from the current recommender system to estimate the likelihood of users being fraudsters. These probabilities are then applied to calibrate the weight of each user during the training phase of the sequential recommender system. Through a process of iterative refinement, LoRec effectively diminishes the impact of fraudsters. Our extensive experimental analysis shows that LoRec, as a general framework, enhances the robustness of sequential recommender systems against poisoning attacks while also preserving recommendation performance.

REFERENCES

- [1] Alex Beutel, Paul Covington, Sagar Jain, Can Xu, Jia Li, Vince Gatto, and Ed H Chi. 2018. Latent Cross: Making Use of Context in Recurrent Recommender Systems. In *Proceedings of the 11th ACM International Conference on Web Search and Data Mining*. 46–54.
- [2] Yongjun Chen, Zhiwei Liu, Jia Li, Julian McAuley, and Caiming Xiong. 2022. Intent Contrastive Learning for Sequential Recommendation. In *Proceedings of the ACM Web Conference 2022*. 2172–2182.
- [3] Kyunghyun Cho, Bart Van Merriënboer, Caglar Gulcehre, Dzmitry Bahdanau, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. 2014. Learning Phrase Representations Using RNN Encoder-decoder for Statistical Machine Translation. *arXiv preprint arXiv:1406.1078* (2014).
- [4] Chen-Yao Chung, Ping-Yu Hsu, and Shih-Hsiang Huang. 2013. βP : A Novel Approach to Filter Out Malicious Rating Rofiles from Recommender Systems. *Decision Support Systems* 55, 1 (2013), 314–325.
- [5] Yashar Deldjoo, Markus Schedl, Paolo Cremonesi, and Gabriella Pasi. 2020. Recommender Systems Leveraging Multimedia Content. *Comput. Surveys* 53, 5 (2020), 1–38.
- [6] Wenqi Fan, Zihuai Zhao, Jiatong Li, Yunqing Liu, Xiaowei Mei, Yiqi Wang, Jiliang Tang, and Qing Li. 2023. Recommender Systems in the Era of Large Language Models (llms). *arXiv preprint arXiv:2307.02046* (2023).
- [7] Ruining He, Chen Fang, Zhaowen Wang, and Julian McAuley. 2016. Vista: A Visually, Socially, and Temporally-aware Model for Artistic Recommendation. In *Proceedings of the 10th ACM Conference on Recommender Systems*. 309–316.
- [8] Ruining He and Julian McAuley. 2016. Fusing Similarity Models with Markov Chains for Sparse Sequential Recommendation. In *Proceedings of the 16th International Conference on Data Mining*. 191–200.

- [9] Xiangnan He, Zhankui He, Xiaoyu Du, and Tat-Seng Chua. 2018. Adversarial Personalized Ranking for Recommendation. In *The 41st International ACM SIGIR Conference on Research and Development in Information Retrieval*. 355–364.
- [10] Balázs Hidasi, Alexandros Karatzoglou, Linas Baltrunas, and Domonkos Tikk. 2015. Session-based Recommendations with Recurrent Neural Networks. *arXiv preprint arXiv:1511.06939* (2015).
- [11] Yupeng Hou, Zhankui He, Julian McAuley, and Wayne Xin Zhao. 2023. Learning Vector-Quantized Item Representation for Transferable Sequential Recommenders. In *Proceedings of the ACM Web Conference 2023*. 1162–1171.
- [12] Hai Huang, Jiaming Mu, Neil Zhenqiang Gong, Qi Li, Bin Liu, and Mingwei Xu. 2021. Data Poisoning Attacks to Deep Learning Based Recommender Systems. In *Proceedings 2021 Network and Distributed System Security Symposium*.
- [13] Wenxiang Jiao, Wenxuan Wang, Jen-tse Huang, Xing Wang, and Zhaopeng Tu. 2023. Is ChatGPT a Good Translator? A Preliminary Study. *arXiv preprint arXiv:2301.08745* (2023).
- [14] Wang-Cheng Kang and Julian J. McAuley. 2018. Self-Attentive Sequential Recommendation. In *Proceedings of the 18th International Conference on Data Mining*. 197–206.
- [15] Shyong K Lam and John Riedl. 2004. Shilling Recommender Systems for Fun and Profit. In *Proceedings of the 13th International Conference on World Wide Web*. 393–402.
- [16] Jiatong Li, Yunqing Liu, Wenqi Fan, Xiao-Yong Wei, Hui Liu, Jiliang Tang, and Qing Li. 2023. Empowering Molecule Discovery for Molecule-Caption Translation with Large Language Models: A ChatGPT Perspective. *arXiv preprint arXiv:2306.06615* (2023).
- [17] Ruyu Li, Wenhao Deng, Yu-Jie Cheng, Zheng Yuan, Jiaqi Zhang, and Fajie Yuan. 2023. Exploring the Upper Limits of Text-Based Collaborative Filtering Using Large Language Models: Discoveries and Insights. *arXiv preprint arXiv:2305.11700 abs/2305.11700* (2023).
- [18] Ruirui Li, Xian Wu, and Wei Wang. 2020. Adversarial Learning to Compare: Self-attentive Prospective Customer Recommendation in Location Based Social Networks. In *Proceedings of the 13th International Conference on Web Search and Data Mining*. 349–357.
- [19] Yuli Liu. 2020. Recommending Inferior Results: A General and Feature-Free Model for Spam Detection. In *Proceedings of the 29th ACM International Conference on Information and Knowledge Management*. 955–974.
- [20] Bamshad Mobasher, Robin Burke, Runa Bhumik, and Chad Williams. 2007. Toward Trustworthy Recommender Systems: An Analysis of Attack Models and Algorithm Robustness. *ACM Transactions on Internet Technology* 7, 4 (2007), 23–es.
- [21] Jianmo Ni, Jiacheng Li, and Julian McAuley. 2019. Justifying Recommendations Using Distantly-labeled Reviews and Fine-grained Aspects. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing*. 188–197.
- [22] Wei Niu, James Caverlee, and Haokai Lu. 2018. Neural Personalized Ranking for Image Recommendation. In *Proceedings of the 11th ACM International Conference on Web Search and Data Mining*. 423–431.
- [23] Steffen Rendle, Christoph Freudenthaler, Zeno Gantner, and Lars Schmidt-Thieme. 2012. BPR: Bayesian Personalized Ranking From Implicit Feedback. *arXiv preprint arXiv:1205.2618* (2012).
- [24] Fei Sun, Jun Liu, Jian Wu, Changhua Pei, Xiao Lin, Wenwu Ou, and Peng Jiang. 2019. BERT4Rec: Sequential Recommendation with Bidirectional Encoder Representations from Transformer. In *Proceedings of the 28th ACM International Conference on Information and Knowledge Management*. 1441–1450.
- [25] Jiaxi Tang and Ke Wang. 2018. Personalized Top-n Sequential Recommendation via Convolutional Sequence Embedding. In *Proceedings of the 11th ACM International Conference on Web Search and Data Mining*. 565–573.
- [26] Jiaxi Tang, Hongyi Wen, and Ke Wang. 2020. Revisiting adversarially learned injection attacks against recommender systems. In *Proceedings of the 14th ACM Conference on Recommender Systems*. 318–327.
- [27] Changxin Tian, Yuexiang Xie, Yaliang Li, Nan Yang, and Wayne Xin Zhao. 2022. Learning to Denoise Unreliable Interactions for Graph Collaborative Filtering. In *Proceedings of the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval*. 122–132.
- [28] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention Is All You Need. *Advances in Neural Information Processing Systems* 30 (2017).
- [29] Paul T. von Hippel. 2005. Mean, Median, and Skew: Correcting a Textbook Rule. *Journal of Statistics Education* 13, 2 (2005).
- [30] Hongxin Wei, Renchunzi Xie, Hao Cheng, Lei Feng, Bo An, and Yixuan Li. 2022. Mitigating Neural Network Overconfidence with Logit Normalization. In *Proceedings of the 39th International Conference on Machine Learning (Proceedings of Machine Learning Research, Vol. 162)*, Kamalika Chaudhuri, Stefanie Jegelka, Le Song, Csaba Szepesvári, Gang Niu, and Sivan Sabato (Eds.). PMLR, 23631–23644. <https://proceedings.mlr.press/v162/wei22d.html>
- [31] Chenwang Wu, Defu Lian, Yong Ge, Zhihao Zhu, Enhong Chen, and Senchao Yuan. 2021. Fight Fire with Fire: Towards Robust Recommender Systems via Adversarial Poisoning Training. In *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval*. 1074–1083.
- [32] Fangzhao Wu, Ying Qiao, Jun-Hung Chen, Chuhan Wu, Tao Qi, Jianxun Lian, Danyang Liu, Xing Xie, Jianfeng Gao, Winnie Wu, et al. 2020. Mind: A Large-scale Dataset for News Recommendation. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*. 3597–3606.
- [33] Xu Xie, Fei Sun, Zhaoyang Liu, Shiwen Wu, Jinyang Gao, Jiandong Zhang, Bolin Ding, and Bin Cui. 2022. Contrastive Learning for Sequential Recommendation. In *Proceedings of the 38th International Conference on Data Engineering*. 1259–1273.
- [34] Zhihai Yang, Lin Xu, Zhongmin Cai, and Zongben Xu. 2016. Re-scale AdaBoost for Attack Detection in Collaborative Filtering Recommender Systems. *Knowledge-Based Systems* 100 (2016), 74–88.
- [35] Haibo Ye, Xinjie Li, Yuan Yao, and Hanghang Tong. 2023. Towards Robust Neural Graph Collaborative Filtering via Structure Denoising and Embedding Perturbation. *ACM Transactions on Information Systems* 41, 3 (2023), 1–28.
- [36] Zheng Yuan, Fajie Yuan, Yu Song, Youhua Li, Junchen Fu, Fei Yang, Yunzhu Pan, and Yongxin Ni. 2023. Where to Go Next for Recommender Systems? ID-vs. Modality-based Recommender Models Revisited. In *Proceedings of the 46th International ACM SIGIR Conference on Research and Development in Information Retrieval*. 2639–2649.
- [37] Zhenrui Yue, Huimin Zeng, Ziyi Kou, Lanyu Shang, and Dong Wang. 2022. Defending Substitution-Based Profile Pollution Attacks on Sequential Recommenders. In *Proceedings of the 16th ACM Conference on Recommender Systems*. 59–70.
- [38] Fuzhi Zhang and Quanqiang Zhou. 2014. HHT-SVM: An Online Method for Detecting Profile Injection Attacks in Collaborative Recommender Systems. *Knowledge-Based Systems* 65 (2014), 96–105.
- [39] Kaike Zhang, Qi Cao, Fei Sun, Yunfan Wu, Shuchang Tao, Huawei Shen, and Xueqi Cheng. 2023. Robust Recommender System: A Survey and Future Directions. *arXiv preprint arXiv:2309.02057* (2023).
- [40] Shijie Zhang, Hongzhi Yin, Tong Chen, Quoc Viet Nguyen Hung, Zi Huang, and Lizhen Cui. 2020. GCN-Based User Representation Learning for Unifying Robust Recommendation and Fraudster Detection. In *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*. 689–698.
- [41] Zijian Zhang, Ze Huang, Zhiwei Hu, Xiangyu Zhao, Wanyu Wang, Zitao Liu, Junbo Zhang, S Joe Qin, and Hongwei Zhao. 2023. MLPST: MLP is All You Need for Spatio-Temporal Prediction. In *Proceedings of the 32nd ACM International Conference on Information and Knowledge Management*. 3381–3390.
- [42] Kun Zhou, Hui Wang, Wayne Xin Zhao, Yutao Zhu, Sirui Wang, Fuzheng Zhang, Zhongyuan Wang, and Ji-Rong Wen. 2020. S3-Rec: Self-Supervised Learning for Sequential Recommendation with Mutual Information Maximization. In *Proceedings of the 29th ACM International Conference on Information and Knowledge Management*. 1893–1902.
- [43] Kun Zhou, Hui Yu, Wayne Xin Zhao, and Ji-Rong Wen. 2022. Filter-enhanced MLP is All You Need for Sequential Recommendation. In *Proceedings of the ACM Web Conference 2022*. 2388–2399.