How Fraudster Detection Contributes to Robust Recommendation

Yuni Lai,¹ Kai Zhou¹

¹Dept. of Computing, The Hong Kong Polytechnic University, HKSAR
csylai@comp.polyu.edu.hk, kaizhou@polyu.edu.hk

Abstract

The adversarial robustness of recommendation systems under node injection attacks has received considerable research attention. Recently, a robust recommendation system GraphRfi was proposed, and it was shown that GraphRfi could successfully mitigate the effects of injected fake users in the system. Unfortunately, we demonstrate that GraphRfi is still vulnerable to attacks due to the supervised nature of its fraudster detection component. Specifically, we propose a new attack metaC against GraphRfi, and further analyze why GraphRfi fails under such an attack. Based on the insights we obtained from the vulnerability analysis, we build a new robust recommendation system PDR by re-designing the fraudster detection component. Comprehensive experiments show that our defense approach outperforms other benchmark methods under attacks. Overall, our research demonstrates an effective framework of integrating fraudster detection into recommendation to achieve adversarial robustness.

Introduction

Recommendation System (RS) has become an indispensable component in online-shopping platforms such as Amazon, Taobao, and eBay. An RS is able to recommend potentially interesting items to a customer based on her browsing history, such as the items she has clicked and the ratings/reviews she has given. While considerable research efforts have been devoted to designing more sophisticated techniques (e.g., based on matrix factorization (Koren, Bell, and Volinsky 2009; Xue et al. 2017; Mehta and Rana 2017) or graph neural networks (Wu et al. 2020; Gao et al. 2022; Wang et al. 2019)) to improve recommendation performance, there is a need to investigate the robustness of RS in an adversarial environment. For one thing, as RS is often related to profits, attackers have enough incentives to attack RS to promote some targeted items, for instance. For another, it is fairly easy for attackers to manipulate customers’ browsing/buying histories to launch those attacks. Indeed, we have seen many node injection attacks against RS (Zhang et al. 2021c, 2020a; Song et al. 2020; Si and Li 2018), where fake nodes (i.e., users or customers) are injected with carefully manipulated ratings to purposely change the recommendation results.

Accordingly, defense mechanisms against such node injection attacks roughly follow two lines: robust training and filtering defense. The former aims to train optimized model parameters such that the model is robust to attacks, where the typical method is through adversarial training (Anelli et al. 2022). The latter focuses on filtering out injected users or mitigating their effects through anomaly detection techniques. Following the second line, one of the state-of-the-art robust models based on Graph Neural Networks (GNNs), termed GraphRfi (Zhang et al. 2020b), was proposed to defend against node injection attacks. At a high level, GraphRfi attaches a fraudster detection component to a GNN-based recommendation component. The detection component takes the user embeddings learned from GNN as input and produce the anomaly probability of each user. This probability is used as a weight for that user in the training objective function for recommendation so that it reflects how much that user contributes to recommendation. Intuitively, by assigning low weights (i.e., high anomaly probabilities) to fake users, one can mitigate the effects of injected fake users. In GraphRfi, the two components were trained in an end-to-end manner to optimize the recommendation performance, and it achieved state-of-the-art results.

Unfortunately, we demonstrate that GraphRfi is still vulnerable to node injection attack. The underlying reason, as we show in Section Why GraphRfi Fails, is that the fraudster detection component utilized a supervised learning method, and its powerful ability of anomaly detection crucially relies on the availability of initial users labels (i.e., fake or normal). However, obtaining these true labels in the real world is extremely hard, if not impossible. For example, even if we can use some unsupervised anomaly detection methods to preprocess the data to label those users, the results may contain errors. The consequence is that the user labels are noisy in that some fake users are labeled as normal, which causes the mis-functioning of GraphRfi as it will assign large weights to those fake users due to its supervised nature.

Our first main contribution is to show the ineffectiveness of GraphRfi by designing a powerful node injection attack. Specifically, we formulate the attack as a bi-level combinatorial optimization problem and propose a gradient-based method to solve it. In particular, one of the main challenges is to compute the required gradients. We adapt the idea of meta-gradients proposed in metattack (Zügner
and Gümennemann 2018). Different from metattack, we not only need to decide the optimal injected edges between fake users and items but also the optimal rating associated with each edge. Our solution is to use a continuous rating tensor to encode all discrete ratings, and after optimization, we use discretization techniques to recover the desired ratings. We term our attack as metaC (representing Continuous metaC). Our experiments show that metaC is very effective in promoting targeted items even with small budgets against the robust model GraphRfi.

Then, based on our vulnerability analysis of GraphRfi, we build up a robust recommendation system termed Posterior Detection-Recommendation system (PDR). In particular, we re-designed the fraudster detection component. The significant difference is that we treat the input user labels as observed but changeable variables (priors). We then use a Implicit Posterior (IP) model (Rolf et al. 2022) to estimate the posterior probability of the true label. Furthermore, we use a strategy to dynamically adjust the prior labels based on the estimated posterior probabilities to counter the noise with posterior. The effect is that even the input labels are noisy, they can be properly adjusted during the training process. Consequently, the fake users (even though labeled as normal) would have fewer contributions to recommendation, which makes our proposed PDR robust against attacks. Our comprehensive experiments show that PDR can successfully defend against metaC and significantly outperforms other defense baselines.

In summary, we propose a new attack method metaC to demonstrate the vulnerability of the state-of-the-art robust recommendation system GraphRfi. We conduct insightful analysis on the ineffectiveness of GraphRfi. Based on the analysis, we design a new robust recommendation system PDR that is tested effective in defending against attacks. Importantly, we demonstrate how fraudster detection could be carefully integrated into recommendation system to improve its adversarial robustness. Rooted from this research, we envision a general framework to achieve robustness for possibly other learning system by incorporating an anomaly detection component that can dynamically adjust the contributions of data points.

Related Works

Attacks on Recommendation System

Injecting nodes into the recommendation system is the major attacking approach as it could be easily implemented in practice by, e.g., creating fake user profiles. The difficulty, however, lies in generating the features of nodes and the ratings they give. Earlier attacks (Li et al. 2016; Sundar et al. 2020) rely on handcrafting those features and giving the highest/lowest ratings to the target items, depending on the goal of pushing or nuking items. However, these fake nodes are prone to be detected as shown in (Rezaimeh and Dadkhah 2021; Wu et al. 2021a,c).

Recently, more sophisticated methods have been proposed, such as optimization, generative models, and so on. For example, representative works (Christakopoulou and Banerjee 2019; Wu et al. 2021c) utilize generative models to generate fake users with the additional goal of remaining stealthy: the embeddings of the fake users and normal ones are pushed to be similar. In particular, Wu et al. (2021a) proposed a GAN-based attack that can not only fulfill the attack goal but also evade anomaly detection. These results actually greatly motivate our research: defending node injection attacks by preprocessing the data to filter out the fake users using anomaly detection is generally not easy.

Defenses on Recommender System

The primary method to achieve the adversarial robustness of recommendation system is through adversarial training which has been tested effective in many other machine learning systems. He et al. (2018) and Tang et al. (2019) perform adversarial training by adding perturbation noise to model parameters in each training iteration to improve the robustness of different target models. Wu et al. (2021b) propose to inject some carefully designed defense users to mitigate the effects of fake users and is targeted at matrix-factorization-based RS.

A topic closely related to defense is anomaly detection, as it is a natural idea to detect the injected fake users. Basically, anomaly detection methods (Burke et al. 2006; Yu et al. 2021) extract the feature of users according to the behavior of the users, such as the degree, rating time, and review content, and then apply classification techniques to identify the abnormal users. Due to difficulty in obtaining the label, unsupervised methods such as clustering (Mehta 2007; Zhang and Kulkarni 2014; Hao and Zhang 2021; Zhang et al. 2021a) and semi-supervised methods (Wu et al. 2012; Cao et al. 2013) are widely-used in detection. However, we emphasize that anomaly detection is often employed as a preprocessing step.

Background

In this section, we provide the necessary background on the target recommendation system that we aim to investigate. Then, we introduce our threat model defining the adversarial environment that the RS operates in.

Target Recommendation System

A Recommendation System (RS) is typically modeled as a weighted bipartite graph \( \mathcal{G} = (\mathcal{U} \cup \mathcal{V}, \mathcal{E}) \), where \( \mathcal{U} = \{u_1, \ldots, u_n\} \) is a set of \( n \) users, \( \mathcal{V} = \{v_1, \ldots, v_m\} \) is a set of \( m \) items, and the edge set \( \mathcal{E} = \{e_{ij} = (u_i, v_j, r_{ij})\} \) is a collection of observed ratings with \( r_{ij} \in \mathbb{R} \) denoting the rating from user \( u_i \) to item \( v_j \). In addition, in some recommendation systems, each user \( u_i \) is also associated with a feature vector \( x_i \), summarizing this user’s behavioral information. The task of recommendation thus amounts to predicting the weights of missing edges and recommending highly ranked items to users.

Since recommendation is often accompanied by interests, RS becomes the common target of node injection attacks, where the attacker would inject some fake users along with carefully crafted ratings to promote/demote some targeted items. To mitigate such attacks, a robust RS GraphRfi (Zhang et al. 2020b) was introduced that combines recommendation with fraudster (i.e., fake users) detection. In particular, GraphRfi has two essential components: a rating prediction component based on Graph Convo-
lutional Networks (GCNs) and a fraudster detection component based on Random Neural Forest (RNF). The main idea of GraphRfi is to treat the anomaly score of a user (from the fraudster detection component) as her weight in estimating the ratings, thus mitigating the effects of anomalous users.

To this end, GCNs are used to learn the embeddings of both users and items, denoted as $z_u$ and $z_v$, which are further used to compute the predicted rating from a user $u$ to an item $v$, denoted as $r'_{uv}$, through an MLP layer. Then, the detection component will take the user embedding and the prediction error $e_{uv} = |r'_{uv} - r_{uv}|$ as input to produce a refined embedding $z'_u$ for user $u$. RNF is then used to compute the conditional probability that a user $u$ is a normal as $P_T[y = 0|z'_u, \theta, \pi]$, where $z'_u$ is the refined user embedding, $\theta$ is the trainable model parameter, $\pi$ is a prior distribution, and $y = 0$ indicates that a user is normal. Finally, the prediction and detection components are jointly trained in an end-to-end manner by minimizing the following loss function decomposed into two parts:

$$L = L_{\text{rating}} + \lambda \cdot L_{\text{fraudster}}$$

$$= \frac{1}{|E|} \sum_{u,v \in E} P_T[y = 0|z'_u, \theta, \pi] \cdot (r'_{uv} - r_{uv})^2 + \frac{1}{|U|} \sum_{u \in U} -\log P_T[y = y_u|z'_u, \theta, \pi],$$

where $L_{\text{rating}}$ summarizes the prediction errors and $L_{\text{fraudster}}$ is the cross-entropy loss with $y_u$ denoting the ground-truth label of user $u$.

We can easily see that the probability $P_T[y = 0|z'_u, \theta, \pi]$ serves as the weight for user $u$. As a result, a user with a high anomaly score (i.e., $1 - P_T$) will contribute less to the prediction, which can enhance the robustness of recommendation under node injection attacks. We can also notice that the fraudster detection component is supervised in nature as the ground-truth labels are required during training; later, we will show the defects of this design.

**Adversarial Environment**

In this section, we introduce the adversarial environment that a recommendation system operates in. We consider an adversarial environment consisting of an attacker and a defender, where the attacker launches node injection attacks against a target RS while the defender (e.g., system administrator) aims to effectively run the RS in the presence of this proactive attacker. Below, we specify the goal, knowledge, and ability of both the attacker and defender, respectively.

**Attacker** We consider an attacker whose goal is to promote a set of target items $T \subset V$. More specifically, the attacker aims to increase the probability that a target item $v_t \in T$ appears in the top-$K$ recommendation lists of target users. Based on the Kerckhoffs’s principle, we assume a worst-case scenario where the attacker has a full knowledge of the target RS, including the data (i.e., the original clean graph $G$) and the recommendation algorithm. To achieve the malicious goal, the attacker is able to inject a set of fake users $U'$ as well as some ratings (i.e., edges $E'$ between $U'$ and $V$), resulting a manipulated graph $G' = (U \cup U' \cup V, E \cup E')$. To constrain the attacker’s ability, we assume that there are at most $H$ fake users (i.e., $|U'| \leq H$), and each fake user can give at most $B$ ratings. After the attack, the defender observes the manipulated graph $G'$, from which the RS is trained and tested; this attack falls into the category of data poisoning attacks.

**Defender** The defender can only observe the poisoned graph $G'$ instead of the clean one $G$. The goal of the defender is to train a robust RS over $G'$ that can mitigate the malicious effects of the injected fake users. Specifically, it is expected that with the robust RS, the target items would not be significantly promoted. We note that the defender does not know which the target items are, and we only use such information for evaluation purpose. In practice, it is common for the defender to run anomaly detection systems to filter out fraudsters before recommending. To reflect this fact, we assume that the defender can identify a fraction $\tau$ ($0 \% \leq \tau \leq 100\%$) of fake users reliably. This parameter $\tau$ indicates the defender’s prior knowledge about the attacks; however, we emphasize that our proposed robust RS works even when $\tau = 30\%$.

**Poisoning Attacks against Recommendation**

**Attack Formulation**

We begin by quantifying the attacker’s malicious goal. Recall that the attacker aims to promote a set of target items $T$. A commonly used metric to measure the effectiveness of recommendation for an item is the hit ratio. Specifically, a hit ratio for an item $v$ with parameter $k$ (denoted as $HR@k(v, G, \theta)$) is the percentage of users whose top-$k$ recommendation list includes that item. Note that we make explicit the dependency of the hit ratio of $v$ on the graph $G$ and the trained model parameter $\theta$. Thus, we can use an adversarial objective function $F_{adv}(G, T, \theta) = \frac{1}{|T|} \sum_{v \in T} HR@k(v, G, \theta)$, the average hit ratios of those target items, to quantify the attacker’s goal.

Poisoning attacks against recommendation then amount to finding the optimal poisoned graph $G'$ to maximize the adversarial objective function. It can be formulated as a bi-level optimization problem, where at the outer level the attacker optimizes the objective over the graph $G'$ while at the inner level, the model parameter $\theta$ is optimized though minimizing the training loss, also depending on $G'$. Mathematically, a poisoning attack can be formulated as

$$\max_{G'} F_{adv}(G, T, \theta^*) = \frac{1}{|T|} \sum_{v \in T} HR@k(v, G', \theta^*)$$

$$\text{s.t.} \quad \theta^* = \arg \min_{\theta} \mathcal{L}(\theta, G'), \quad G' = G \cup U' \cup E', \quad |U'| \leq H, \quad d(u') \leq B, \forall u' \in U',$$

where we use $G' = G \cup U' \cup E'$ to denote that $G'$ is obtained by injecting a set of fake users $U'$ and edges $E'$ into $G$, $|U'| \leq H$ requires that at most $H$ fake users are injected, and the degree $d(u') \leq B$ requires that each fake user can give at most $B$ ratings.
One major challenge in solving the above optimization problem is that the searching space is discrete and exponential in the size of $G$: the attacker needs to determine which items to rate as well as the specific discrete ratings (e.g., scale 1 to 5). We thus use a series of techniques to approximate this discrete optimization problem. First, we use a continuous probability vector $r$ to encode a discrete rating value. For example, suppose the rating values ranges from 1 to $K$, we use $r = (p_1, p_2, \ldots, p_t, \ldots, p_K)$ to denote that a user will give a rating $l = 1, 2, \ldots, L$ with probability $p_l$. Then, we assume that the injected users will initially connect to all items. Thus, the attacker’s behavior is now fully captured by a rating tensor $\hat{r} \in [0, 1]^{[d'] \times |V| \times L}$. We denote the manipulated graph as $\hat{G} = G \cup U' \cup \hat{r}$. Another difficulty comes from the non-differentiability of the objective function, in particular, the hit ratios. Thus, we use a sum of soft-max function ratios (Tang, Wen, and Wang 2020) to approximate $F_{adv} (G, T, \theta^*)$, as below:

$$L_{adv} (\hat{G}, T, \theta^*) = - \sum_{i \in U} \sum_{l \in L} \log \left( \frac{\exp (r_{il}')} {\sum_{u \in V} \exp (r_{ul}')} \right),$$

where $r_{il}'$ denotes the predicted rating from user $u$ to $v$. Basically, this function measure the fraction of the ratings for targeted items over the ratings for all items. Now, the optimization problem (2) can be re formulated as

$$\min_{\hat{r}} L_{adv} (\hat{G}, T, \theta^*) \quad (4)$$

$$s.t. \quad \theta^* = \arg \min_{\theta} L (\theta, \hat{G}), \quad \hat{G} = G \cup U' \cup \hat{r}, \quad \sum_{l} \hat{r}_{i,j,l} = 1, \quad \hat{r} \in [0, 1]^{[d'] \times |V| \times L}. $$

Below, we introduce the method to solve problem (4) to obtain the (sub-)optimal continuous rating tensor $\hat{r}$, from which we can derive the discrete ratings that satisfy all the constraints.

**Optimization Method** We utilize an iterative optimization paradigm based on gradient descent to solve the bi-level optimization problem. Specifically, we iteratively update the inner objective $L_\theta (\cdot)$ with respect to $\theta$ for $k_1$ steps and update the outer objective $L_{adv} (\cdot)$ with respect to $\hat{r}$ for $k_2$ steps, where $k_1$ and $k_2$ are hyper-parameters. However, a central challenge of updating $L_{adv} (\cdot)$ lies in computing the gradients of $L_{adv} (\cdot)$ with respect to $\hat{r}$. Specifically, based on the chain rule of derivation, computing the gradients of $\theta^*$ with respect to $\hat{r}$ is time-consuming as $\theta^*$ itself is obtained through an optimization process depending on $\hat{G}$. To address this issue, we adopt the idea of approximating meta gradients proposed by Zügner and Günnemann (2018) to compute the required gradients. In detail, in each step of updating $L_{adv}$, the parameter $\theta$ is updated for $k_1$ steps in the inner layer. We denote the trajectory of updates as $\theta^1, \theta^2, \ldots, \theta^{k_1}$ and we further assume that these parameters are independent. This allows us to compute the gradient of $L_{adv}$ with respect to $\hat{r}$ under a fixed parameter $\theta^t$, denoted as $\nabla_{\hat{r}} L_{adv} (\hat{G}, T, \theta^t)$. Then, we use the sum of the gradients during the $k_1$ steps of updates as the approximation, termed as meta-gradients:

$$\nabla_{\hat{r}} L_{adv} (\hat{G}, T, \theta^t) \approx \nabla_{\hat{r}} L_{adv} (\hat{G}, T, \theta^t).$$

As a result, we can update $L_{adv}$ for one single step in the outer layer based on meta-gradients:

$$\hat{r}^{t+1} = \hat{r}^t - \eta \nabla_{\hat{r}} L_{adv} (\hat{G}, T, \theta^t),$$

where $\eta$ is the learning rate. We can then iteratively update $\hat{r}$ and $\theta$ until the loss $L_{adv}$ diminishes to an acceptable level.

The above iterative method allows us to update the rating tensor $\hat{r}$ based on gradients. However, there are two additional issues that need to be addressed. First, during optimization, we need to ensure that the entries in $\hat{r}$ should always within the range of $[0, 1]$ and sum to 1 while gradient updates might break these constraints. To this end, after each gradient update, we project each entry to $[0, 1]$ and apply the following widely used 0-1 normalization method to all entries:

$$\hat{r}_{i,j,l} = \frac{\hat{r}_{i,j,l} - \min (\hat{r}_{i,j,l})} {\max (\hat{r}_{i,j,l}) - \min (\hat{r}_{i,j,l})}, \quad \hat{r}_{i,j,l} = \frac{\hat{r}_{i,j,l}} {\sum_{l=1}^{N} \hat{r}_{i,j,l}}.$$ 

These operations ensure that the entries of $\hat{r}$ could be interpreted as the probabilities of adding certain ratings during optimization. Second, after optimization, we will need to discretize the ratings and simultaneously pick $B$ ratings for each fake user. While various methods exist, we found in our experiments that simply selecting the rating value is the highest probability could achieve the best attack performance. Specifically, given the optimized rating tensor $\hat{r}$, we discretize each rating vector $\hat{r}_{ij}$ as $(l, p_l)$, where $p_l = \max (\hat{r}_{ij})$ and $l$ is the corresponding index of $p_l$. Then, for a user $i$, we rank the discrete ratings in descending order of $p_l$ and pick top-$B$ as the injected ratings.

In summary, we formulate the node injection poisoning attack as a bi-level optimization problem which is solved by an iterative optimization method in the continuous domain. Through discretization, we finally obtain the injected users associated with ratings, i.e., a poisoned graph $\bar{G}'$.

**Why GraphRfi Fails**

The robust recommendation model GraphRfi relies on an integrated anomaly detection component to defend against injected fake users. Specially, the anomaly detection component is trained together with the rating prediction component in an end-to-end manner. During training, the anomaly detection component assigns an anomaly score to each data point (i.e., a user), which is inversely proportional to the contribution of that data point to prediction. Supposedly, those fake users would be assigned a large anomaly score at the end of training, thus having little effect on prediction. Indeed, GraphRfi accomplished this task very effectively – only when those fake users were correctly labeled.
The underlying reason that GraphRfi fails against our proposed poisoning attack is that its anomaly detection component adopts a supervised learning approach. As a result, if a user is labeled as normal (even if it is actually fake), supervised learning will eventually assign a small anomaly score to it as the training process continues. That is, fake users that are labeled as normal would still have strong malicious effects on the prediction.

We conduct comprehensive experiments to demonstrate this phenomenon. Specifically, we can classify the users into four types. Type I and Type II users are normal and anomalous users inherently existing in the graph, respectively, and the defender knows their labels reliably. Among the injected fake users, a fraction of \( \tau \) users (denoted as Type III) are determined as anomalous with high confidence by the defender and thus are labeled as abnormal. The rest of the fake users (denoted as Type IV) are labeled as normal. We emphasize that the parameter \( \tau \) is a variable that reflects the defender’s ability to identify abnormal users from the collected data, and in practice, it is not uncommon that \( \tau \) is low especially when there are several effective stealthy node injection attacks against recommendation systems.

We observed the anomaly scores for those four types of users during the whole training process of GraphRfi, shown in Fig. 3a. We can observe that Type II and Type III users (labeled as fake) have very high anomaly scores during training. In comparison, the anomaly scores of Type IV users (fake but labeled as normal) keep decreasing as training continues and eventually approach to those of Type I users (normal).

In summary, the insufficient ability of a defender to filter out fake users (which is common) resulted in highly noisy user labels and further caused the supervised anomaly detection component to assign low anomaly scores (i.e., large weights of contribution) to evaded fake users, which finally left GraphRfi vulnerable to poisoning attacks. This crucial observation also guides us in designing robust recommendation systems.

### Robust Recommendation under Attack

Our previous analysis shows that the inability to correctly labeling all fake users causes the failure of GraphRfi. In this section, we propose techniques to resolve this issue with the goal of building a robust recommendation system.

Similar to GraphRfi, we utilize an anomaly detection component within the recommendation system which takes the noisy labels and user embeddings as inputs, and outputs the anomaly probabilities. At a high level, our anomaly detection component combines two procedures: posterior probability estimation and dynamic label adjustment. Specifically, we assume that a label associative with a user is a variable instead of being fixed. We treat the given noisy labels (termed as soft labels as they will be adjusted later) as observable priors and the unknown true labels as latent variables. Thus, given the noisy labels, we can use a model to estimate the posterior probabilities of the true labels. Then, based on the estimated posterior probabilities, we use a strategy to dynamical adjust the soft labels (priors) during the end-to-end training process in order to more accurately estimate the posterior probabilities. Below, we articulate the details of the two procedures.

#### Posterior probability estimation

We aim to estimate the true labels based on the observed user features \( x_u \) and their noisy labels. Here we set \( x_u \) as the embedding \( z_u \) produced by GCN. We define the latent label of user \( u \) as a variable \( l_u \in C = \{f, n\} \), where \( f \) and \( n \) represent fake and normal, respectively. The prior probability of this label \( l_u \) is represented as a two-dimensional vector \( p(l_u|x_u) = [p(l_u = f), p(l_u = n)] \), where we make the dependency of \( l_u \) on \( x_u \) explicit. To take into account that the observed labels are noisy, we initialize the prior probabilities as follows. For a user with a given label \( f \), we set \( p(l_u|x_u) = [1 - p_0, p_0] \) (instead of \([1, 0]\\), where \( p_0 \) is the probability that a user labeled with fake is actually normal. Similarly, for a normal user, we set \( p(l_u|x_u) = [p_1, 1 - p_1] \), where \( p_1 \) is the probability that a user labeled with normal is actually fake. We note that \( p_0 \) and \( p_1 \) are hyper-parameters of the system that depend on the anomaly detection system used to preprocess the data. We denote the estimated posterior probability of the label as \( q(l_u|x_u) = \arg max_{l_u \in C} p(l_u|x_u) \).

We adopt the Implicit Posterior (IP) model (Rolf et al. 2022) to estimate the posterior probability \( q(l_u|x_u) \) based on the prior \( p(l_u|x_u) \). IP was initially proposed to address the label uncertainty problem in image classification/segmentation tasks. Specifically, Rolf et al. (2022) parameterized \( q(l_u|x_u) \) by a neural network. Based on the negated evidence lower bound (ELBO), the IP loss function can be constructed as

\[
\mathcal{L}_{IP} = \sum_{u \in \mathcal{U}, c \in C} \left( q_0(l_u = c|x_u) \log \frac{\sum_{j \in \mathcal{C}} q_0(l_j = c|z_u; \theta)}{p(l_u = c|x_u)} \right),
\]

where \( \theta \) denotes the trainable parameters of neural network, and \( q_0(l_u = c|x_u) := q(l_u = c|x_u; \theta) \). The minimization of the IP loss will lead to the maximization of log-likelihood regarding all observed data \( x_u \). We use this \( \mathcal{L}_{IP} \) loss to train our fraudster detection component which will output the estimated posterior probability \( q(l_u|x_u) \) for each user \( u \). To integrate the IP model in recommendation, we substitute the \( L_{\text{fraudster}} \) in Eqn (1) with the IP loss. We use a two-layer fully-connected neural network followed by a soft-max layer with temperature \( T \) to implement this detection model. We use temperature scaling as proposed (Keren, Cummins, and Schuller 2018) to calibrate the prediction confidence.

#### Dynamic label adjustment

We use another technique to more accurately estimate \( q(l_u|x_u) \). We observed in our experiments that as the training continues, the posterior probabilities learned by neural network will eventually approach to the priors, probably due to the over-fitting of neural networks. To address this, we will use the highly confident posterior to correct the errors (noise) in the priors. In other words, we will update a soft label (prior) if the corresponding posterior is of high confidence. Specifically, we will update the soft labels in iterations along with the training process. For ease of presentation, we use \( p(f_u|l_u) \), \( q(f_u|l_u) \), and...
Table 1: Statistics of YelpCHI and Movies

|          | # users | # items | # edges | # fake users |
|----------|---------|---------|---------|--------------|
| YelpCHI  | 38063   | 201     | 67395   | 7739         |
| Movies   | 39578   | 71187   | 232082  | 19090        |

\[ p(n_u)^t, \text{ and } q(n_u)^t \text{ as the simplicity of } p(l_u = f), q(l_u = f), p(l_u = n), \text{ and } q(l_u = n) \text{ in the } t\text{-th iteration, respectively. We update } p(f_u) \text{ according to the following strategy:} \]

\[
p(f_u)^{t+1} = \begin{cases} 
(1 - \alpha) p(f_u)^t - \alpha (1 - q(f_u)^t), & q(f_u)^t < c_1 \\
(1 - \alpha) p(f_u)^t + \alpha q(f_u)^t, & q(f_u)^t > c_2 \\
p(f_u)^t, & \text{otherwise.} 
\end{cases}
\]

Basically, we use intervals \([0, c_1]\) and \([c_2, 1]\) to determine whether the estimation of \(q(f_u)^t\) is confident or not. In particular, if \(q(f_u)^t\) is higher than an upper-threshold \(c_2\), we increase its prior probability \(p(f_u)^t \rightarrow (1 - \alpha)p(f_u)^t + \alpha q(f_u)^t\), where \(0 < \alpha < 1\) is an update rate that controls the adjustment speed (i.e., the effect of \(q(f_u)^t\) is discounted by \(\alpha\)). Similarly, if \(q(f_u)^t\) is smaller than a lower-threshold \(c_1\), we decrease \(p(f_u)^t \rightarrow (1 - \alpha)p(f_u)^t - \alpha (1 - q(f_u)^t)\). We set \(p(n_u)^t + 1\) as \(1 - p(f_u)^t + 1\). We apply this dynamic label adjustment after the detection AUC (Area Under Curve) on the testing set first reaches \(a_0\) that the model has a good performance but before over-fitting, where \(0.5 < a_0 < 1\) is a hyper-parameter.

**Experiments**

In this section, we evaluate the performances of both our proposed attack and robust recommendation system.

**Datasets and Experiment Settings**

**Datasets** We conduct experiments over two widely-used real-world datasets YelpCHI and Amazon Movies&TV (abbreviated as Movies). Specifically, YelpCHI contains around 60,000 reviews/ratings regarding 201 restaurants and hotels in Chicago from 38,063 reviewers. Each rating is ranged from 1 to 5 and the corresponding review is provided with a label of fake or normal. In our setting, we treat a user giving fake review(s) as fake. The other dataset Movies contains views from Amazon under the category of Movie&TV. Each review, with a rating from 1 to 5, is voted helpful/unhelpful by other users, which provides the information to determine whether a user is fake or normal. Specifically, we only consider the reviews with more than 20 votes. If more than 70% of the votes of a review are helpful, we regard it as normal; otherwise, fake. Same as above, we treat the users giving fake review(s) as fake users. The statistics of the two datasets are summarized in Table 1.

**Settings** Following the typical settings | (Zhang et al. 2021b), we randomly sample 5 items from all as the targets. To train the RS model, we randomly sample 20% of existing ratings labeled with normal as the testing set, and the remaining are the training set. The budget of each injected user is \(B = 15\). The experiments are repeated for 5 times with different random seeds. More parameter settings are detailed in the supplement.

**Benchmark Methods**

**Attack** We compare to three common attack methods as suggested in (Wu et al. 2021c): Random Attack, Average Attack, and Popular/Bandwagon Attack. In all these attacks, a fake user gives highest ratings to the target items and a set of filler items using the remaining budget. In Random Attack, filler items are randomly selected, and the corresponding ratings are sampled from a normal distribution \(N(\mu, \sigma^2)\), where \(\mu\) and \(\sigma\) are the mean and deviation of all existing ratings. For Average Attack, the only difference from Random Attack is that the rating given to a filler item \(v_i\) is sampled from \(N(\mu_{v_i}, \sigma_{v_i})\), where \(\mu_{v_i}, \sigma_{v_i}\) are the means and deviation of existing ratings for item \(v_i\). In Popular Attack, a portion (set as 30% in our experiment) of filler items are selected as popular items since they might have bigger impacts, and the ratings given to these popular items are also set as \(r_{max}\).

**Defense** We compare PDR with two representative defense approaches. First, for the category of adversarial training, Wu et al. (2021b) was specifically designed for matrix-factorization-based RS which is much more lightweight than GNN-based systems. As a result, adapt their approach to our target model would incur severe computational overhead. Instead, we use another representative approach of adversarial training proposed by Yuan, Yao, and Benatallah (2019). Specifically, it will pre-train the target model and then adds perturbation noise to the model parameters while training the model.

Second, we explore the idea of using the result of anomaly detection for defense. The natural idea is to remove the detected fake users from the system. Note that, we do not constrain a specific method here for anomaly detection; instead, we assume that a fraction \(\tau\) of the injected fake users can be detected since any attack methods might be employed by attackers. In our experiment, this fraction of fake users are removed; we thus term this approach as Remove Anomaly.

**Attack Performance of MetaC**

We use the averaged hit ratios of the target items, i.e., \(HR@10\) and \(HR@50\), as the metrics to evaluate how the attacks can promote target items. We test the attack performances over various attack powers (0.0%, 0.3%, 0.5%, 0.7%, 1.0%, 2.0%), where the attack power represents the fraction of the number injected users over all users. In this section, the fraction of injected fake users with correct labels is set as \(\tau = 30\%\) to reflect that a user deploying GraphRi may have some prior knowledge about the data. However, later we show that GraphRi can be successfully attacked regardless of the value of \(\tau\). The hit ratios under attack (the higher, the better) are presented in Fig. 1. We can see that MetaC achieves the best attack performances in all cases, especially on Movies. In general, the gaps between MetaC and others are more evident when using \(HR@10\) as the metric since pushing items to the top-10 is much harder than
pushing to the top-50, which actually demonstrates the effectiveness of MetaC.

**Defense Performance of PDR**

The defense goal is to retain the hit ratios of the target items under attack. Fig. 2 presents the performances of different defense approaches under various attack powers. We can see that PDR achieves the best defense performance, especially when the attack power is higher (it is also when defense is harder). We note that Remove Anomaly may or may not be better than GraphRfi (i.e., without defense). The reason is that the anomaly detection component within GraphRfi is supervised. Thus, removing the correctly labeled fake users, as Remove Anomaly did, reduces the supervision, which might harm the performance. This actually demonstrates the significance of our proposed way of dealing with those detected fake users.

**Why PDR is robust**

The adversarial robustness of PDR comes from the fact that it can detect and dynamically adjust the contributions of fake users in the recommendation system. To show this, we visualize the trajectories of anomaly scores (inversely proportional to contribution) of different types of users during the training of two systems GraphRfi and PDR in Fig. 3a and Fig. 3b, respectively. What we should focus on is the Type IV users (i.e., fake users but labeled as normal), the anomaly scores of which are shown in red over YelpCHI. Compared to GraphRfi, PDR can assign large anomaly scores even for Type IV users, which is the reason for its adversarial robustness. The results over Movies are similar and are shown in the supplement.

**Influence of Prior Knowledge**

In the experiments, we use a parameter \(\tau\) to control the defender’s prior knowledge (possibly obtained from using some anomaly detection methods to preprocess the data) regarding the injected fake users. Specifically, \(\tau\) is the recall over injected users defined as \(\tau = \frac{|\{u \in L' | \text{labeled as fake}\}|}{|L'|}\), representing the fraction of fake users that are correctly labeled. We thus evaluate the two different ways (i.e., Remove Anomaly and PDR) of dealing with detected fake users under different levels of \(\tau\). Fig. 4 shows that PDR achieves the best performance over YelpCHI and the performance becomes better as \(\tau\) increases as it receives more supervision. Again, Remove Anomaly is not quite effective in some cases as removing correctly labeled fake users also decreases the supervision. The results over Movies are similar and are shown in the supplement.

**Conclusion and Future Work**

In this paper, we demonstrated the vulnerabilities of a state-of-the-art robust recommendation system called GraphRfi by designing an effective attack approach MetaC. We showed that the vulnerabilities come from the supervised nature of its fraudster detection component. We thus re-designed the detection component which is equipped with the ability to dynamically adjust the importance of newly injected fake users, resulting in a robust RS PDR. This research demonstrated the effectiveness of a framework of integrating anomaly detection into learning systems to improve their adversarial robustness. In our future work, we expect to see the successful application of this framework on other learning systems.
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Appendix

MetaC

We further summarize the process of obtaining continuous rating tensor \( \hat{R} \) by alternative iteration in Algorithm 1.

**Algorithm 1: MetaC Poisoning Attack**

**Input:** Initiated rating tensor \( \hat{R} \); Total training epochs \( T_{train} \); Attack interval \( k_1 \)

**Output:** The optimized rating tensor \( \hat{R} \)

for \( t \leftarrow 1 \) to \( T_{train} \) do

for \( j \leftarrow 2 \) to \( k_1 \) do

\[
\theta^{t+1} = \theta^t - \eta_1 \nabla_{\theta} \mathcal{L}_{\text{adv}};
\]

\[
\hat{R}_i,j,l = \frac{\max(R_{i,j,l} - \min(R_{i,j,l}))}{\sum_{l=1}^{\text{max}(R_{i,j,l})} \min(R_{i,j,l})};
\]

\[
\hat{R}_i,j,l = \frac{R_{i,j,l} - \eta_2 \cdot \nabla_{\theta} \mathcal{L}_{\text{adv}}}{\mathcal{L}_{\text{adv}}};
\]

return \( \hat{R} \)

Due to the large volume of the search space in the Movies dataset which has a huge amount of items, the training set during the attack optimization will be much larger. According to Takahashi (2019), two-layers GCN is much more vulnerable to the poisoning nodes within 2-hops, thus we can shrink the space of candidate items as 2-hop neighbors of the target items, which makes the training more efficient.

Data Preprocessing

During the data preprocessing, we iteratively remove the items and users that are less than two records. We extract the user features for initializing GCN following (Zhang et al. 2020).

Experiments Setting

The number of inject user proportion is set to 1% of the original user number and detection fraction \( \tau = 30\% \) if not mentioned. We set the alternative iteration parameters \( k_1 = 100 \), and \( k_2 = 1 \). We totally train the model for \( T_{train} = 50 \) epochs during attack optimization and retraining after poisoning. In the PDR framework, we set the temperature of soft-max as \( T = 2.0 \). We set the probability that a user labeled with fake is actually normal as \( p_0 = 0.01 \), and the probability that a user labeled with normal is actually fake as \( p_1 = 0.2 \). In the label adjustment strategy, we update the labels when the AUC of the detection model reaches \( a_0 = 0.8 \), and we set update rate \( \alpha = 0.05 \). At the beginning, we set the adjust interval parameters \( c_1 = 0.4 \), \( c_2 = 0.85 \), and decreasing \( c_1 \) while increasing \( c_2 \) to decay the range of adjusting interval by \( c_1^{t+1} = \min\{c_1^t - 0.025, 0.2\} \), and \( c_2^{t+1} = \max\{c_2^t + 0.025, 1.0\} \).

Experimental Results

In this part, we provide supplementary experimental results that are not able to present in the paper due to the page limitation.

Defense

We further evaluate the defense effectiveness under different detection power on another dataset Movies and introduce the more detailed setting of Recall. We assume that the beforehand anomaly filtering model (can be an anomaly detection model or filtering by rules such as votes of helpful/unhelpful.) will assign the top 1% of users as fraudsters according to their confidence, and we set different levels of recall (inject user) to stimulate the various detection power, where the recall value of our inject users is equivalent to parameter \( \tau \): Recall (inject user) = \( \tau \) Here, different to our previous setting that only consider mislabeling proportion of inject user, some of the normal users will also be mislabeled as fake. We can observe from Figure 1 that our defense method can lead to the lower HR@10 and HR@50 which is closer to the before attack level most of the time.

Anomaly Scores

We further provide the anomaly scores among four types of users in Movies dataset. Type I and Type...
II users (blue and orange lines) are normal and anomalous users inherently existing in the graph, respectively, and the defender knows their labels reliably. Among the newly injected fake users, a fraction of $\tau = 30\%$ users (denoted as Type III) are determined as anomalous with high confidence by the defender and thus are labeled as abnormal (green lines). The rest of the fake users (denoted as Type IV) are labeled as normal (red lines). Figure 2 shows that, after our defense strategy PDR applied, the mislabeled inject user can have much higher anomaly scores (red lines) compared to GraphRfi.

### Hyper-parameter

To evaluate the sensitivity of hyper-parameter $a_0$ which decides when the label adjustment begins, we conduct experiments based on $a_0$ from 0.7 to 0.9 on the dataset YelpCHI. And the results in Figure 3 show that, the defense effectiveness is robust under different $a_0$.

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