Robust Explainable Recommendation

SAIRAMVINAY VIJAYARAGHAVAN, University of California Davis, USA

PRASANT MOHAPATRA, University of South Florida, Tampa, USA

Explainable Recommender Systems is an important field of study which provides reasons behind the suggested recommendations. Explanations with recommender systems are useful for developers while debugging anomalies within the system and for consumers while interpreting the model's effectiveness in capturing their true preferences towards items. However, most of the existing state-of-the-art (SOTA) explainable recommenders could not retain their explanation capability under noisy circumstances and moreover are not generalizable across different datasets. The robustness of the explanations must be ensured so that certain malicious attackers do not manipulate any high-stake decision scenarios to their advantage, which could cause severe consequences affecting large groups of interest. In this work, we present a general framework for feature-aware explainable recommenders that can withstand external attacks and provide robust and generalized explanations. This paper presents a novel framework which could be utilized as an additional defense tool, preserving the global explainability when subject to model-based white box attacks. Our framework is simple to implement and supports different methods regardless of the internal model structure and intrinsic utility within any model. We experimented our framework on two architecturally different feature-based SOTA explainable algorithms by training them on three popular e-commerce datasets of increasing scales. We noticed that both the algorithms displayed an overall improvement in the quality and robustness of the global explainability under normal as well as noisy environments across all the datasets, indicating the flexibility and mutability of our framework.

CCS Concepts: • General and reference \rightarrow Design; Reliability; • Computing methodologies \rightarrow Neural networks; Factorization methods; • Information systems \rightarrow Recommender systems.

Additional Key Words and Phrases: Recommender Systems, Explainable Recommendation, Robust Recommender Systems, Adversarial Training, Neural Networks , Machine Learning

ACM Reference Format:

Sairamvinay Vijayaraghavan and Prasant Mohapatra. 2024. Robust Explainable Recommendation. 1, 1 (May 2024), 16 pages. https://doi.org/10.1145/nnnnnnnnnnn

1 INTRODUCTION

Explainable Recommender Systems is a subset of Recommender Systems (RS) which provide a special attribute to a regular RS algorithm of explaining the predicted recommendation outcomes. Explanations generated along with the recommendations within any RS framework has multiple practical uses. For example, explanations can be utilized as system diagnostics by developers for detecting fairness disparities within the outcomes [18] and unexpected anomalies within the system which could lead to erroneous and incorrect outcomes [15]. From the consumer's perspective, explanations are an asset in describing the presented outcomes, providing reasons to justify the recommendations indicating how effective is the system in capturing the true preferences of any particular consumer [35, 49, 54]. Hence, explainability is one

Authors' addresses: Sairamvinay Vijayaraghavan, saivijay@ucdavis.edu, University of California Davis, 1 Shields Avenue, Davis, CA, USA, 95616; Prasant Mohapatra, pmohapatra@usf.edu, University of South Florida, Tampa, Tampa, USA.

 $\ensuremath{\textcircled{}^\circ}$ 2024 Association for Computing Machinery.

Manuscript submitted to ACM

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

of the key components that establish trust and confidence within the consumers and developers belonging to an RS realm.

Recent studies have been focussing more on the robustness and generalization of explanations provided by any explainable algorithm [21]. However, while most of the explainable RS keep improving the personalization efficiency of the explainable methods, there are not many direct RS methods that are capable of providing robust and generalized explanations when subject to various noisy conditions such as data corruption, malicious model attacks [5, 17] etc. In addition, most of the existing explainable methods are proven vulnerable empirically, indicating a drop in explainability when subject to strong security based attacks in a recent study [48]. It is very important to provide trustworthy explanations within an RS framework, particularly for both consumers and developers. For example, let us consider a healthcare based recommender system which recommends medicines to patients, additionally providing reasons for the suggested medicines reasoning the relevance, which radiologists and doctors rely on for confirming their medical decisions. However, attackers with malicious intent could possess a sole aim to sabotage the credibility of this system. Explanations can be targeted since they provide an easy but effective way to mislead and distract the medical doctors during high stake decisions. Suppose if the explainable procedure of a system is attacked, then the system could provide incorrect and misleading explanations which could be non-representative of the true cause for suggesting the medicines to a given patient. This would lead to an incorrect identification of the true cause for a given illness which could then delude the doctor to provide medicines which could be irrelevant and not a remedy for the true illness for a patient. Thus, this could lead to some severe consequences, especially under high-stake decision scenarios [12, 29]. Hence, robust explanations are a necessity within any explainable platform, particularly in RS.

In this paper, we present a novel framework that ensures robustness and generalization of the personalized explanations provided in recommenders. We developed this framework with an exclusive focus on a special subset of feature-aware explainable methods in RS, thus allowing our framework to be easy to extend and flexible to adapt. Our framework, which is purely motivated by adversarial training, holds good for all the feature-aware recommenders that follow a similar learning paradigm and prediction template as we suggest in our framework. We conduct our experiments by subjecting the recommenders to white-box-based model attacks. Our main contribution to the field of explainable RS is that we upgrade the general learning paradigm for feature-aware explainable recommenders which would be capable of preserving explanation capabilities under noisy environments. We ensure that we can provide robust and trustworthy explanations and to our best knowledge, we present one of the initial works towards the fresh field of robust explanations in RS. We summarize our contributions as follows:

- We design a flexible framework which could be easily extended to other feature-aware explainable methods, since the key update performed is independent of the training objective of the recommender and it does not require changing the basic intrinsic architecture of the recommender
- We propose an adaptable framework which could achieve the goal of robust explanations at a global level within any RS and developers could additionally include other significant goals within these systems which makes our framework easy to expand.

2 RELATED WORK

2.1 Explainable Recommendation

Explanations within RS have been categorized under various criteria: primarily based on the style and type of the explanations provided. Typically, explanations are provided in the form of generated text sentences [10, 31, 32], paths derived from knowledge graphs [11, 25, 42] or simple interpretable features. We identified two broad categories of feature-aware explanations: intrinsic attention based score explanations [9, 20, 41] and user provided text review-based feature explanations. These described features can be representative of any user's personalized preferences which could be leveraged for explaining the provided suggestions by a RS model. Zhang et al. [56] introduced a sentiment-analysis based method for extracting text features from user provided reviews which identified and highlighted descriptions through the sentiments and adjectives that were used to express their personalized preferences given any particular user-item interaction. This framework of extracting feature explanations had been followed across different explainable recommenders in various ways. For example in [30, 50], the authors have constructed tensors involving the user/item, feature and the opinion with which the feature was expressed within the review, while in [7, 24], this technique was utilized along with attention based mechanisms to aid capturing more complex relations across the features and the outcomes. While most of these works have possessed the key goal of improving the global explainability of the model on a global level, none of these works consider generalizing and improving robustness of these models towards changing circumstances. In this work, we will improve on the existent broad framework which contains all these methods with a purpose of providing more generalized and robust explanations.

2.2 Robust Explanations

Over the previous few years, there has been some progressive work regarding improving reliability of explainable methods, motivated by analyzing the vulnerability of such methods towards external attacks. For example, in [38], Nielsen et al. have explored the behavior of various gradient-based interpretable methods within neural networks under different noisy conditions. Similarly, there are other works that have explored the behavior under attacked conditions of explainable models such as for saliency maps [1, 23, 27, 45] and post-hoc explainable methods [2, 29, 44]. In recent years, there have been research studies that have invented counter strategies for improving the robustness of interpretability, with some works motivated by an analytical observation that the vulnerability within interpretable methods is caused due to the large curvature of the model's decision function [12, 33]. However, majority of the defense training solutions is proposed mostly via adversarial learning techniques. Especially, Ross and Doshi-Velez [40] presented a defense model that includes an additional gradient term of the true loss objective into the training loss which improves the overall robustness and the interpretability of the model together. The similar concept of leveraging adversarial training and studying its effects on the explainability has been explored in depth in these works also [14, 26, 29, 39]. We have also followed the existent defense training strategy by incorporating adversarial objectives within training in order to enhance the robustness of explanations within RS.

3 FEATURE-AWARE EXPLAINABLE RECOMMENDATIONS

Let U be the set of users and V be the set of items of a dataset D. For constructing our features, we utilized the text-based user-written reviews in D which provides features using a relevant sentiment analysis based tool called Sentires [56]. This tool considers all the user-item reviews of D, and extracts the highlighted important aspects f of items, the sentiment score s and qualifying opinion adjectives o, with which the items were reviewed on. The features extracted FManuscript submitted to ACM is the source for generating explanations. The sentiment score belongs to a binary set of whether being expressed in a positive or negative tone, which can be quantified as $\{-1, +1\}$. In order to learn the relationships between the user, item, and the features, we construct the user-aspect matrix $X \in \mathbb{R}^{|U| \times |F|}$ and item-aspect matrix $Y \in \mathbb{R}^{|V| \times |F|}$ as followed by [47, 50, 55, 57]. We express our feature matrix construction technique as follows:

$$\begin{split} X_{u,f} &= \begin{cases} 0 & \text{if f is never mentioned by u} \\ 1 + (N-1)(\frac{2}{1 + \exp(-t_{u,f})} - 1) & \text{else} \end{cases} \\ Y_{v,f} &= \begin{cases} 0 & \text{if v is never reviewed on f} \\ 1 + (\frac{(N-1)}{1 + \exp(-t_{v,f} \cdot w_{v,f})}) & \text{else} \end{cases} \end{split}$$

where N is the maximum rating scale from the reviews (typically 5), $t_{u,f}$ is the number of mentions of the aspect $f \in F$ within reviews from user $u \in U$, $t_{v,f}$ is the number of mentions of the feature $f \in F$ that describes the item $v \in V$, and $w_{v,f}$ is the average sentiment polarity of all the (v, f) mentions.

4 PROPOSED FRAMEWORK FOR ROBUSTIFYING EXPLANATIONS

4.1 Overview

In this section, we discuss our proposed framework for robustifying explanations within feature-aware explainable recommenders. Let us simply represent $L(D:(X;Y)|\Theta)$ be the differentiable loss function of a black-box recommender (predominantly combining the recommendation and explanation utilities of the recommender) of a dataset D, with inputs as the user feature matrix X and item feature matrix Y. We can observe that in general, any explanation procedure depends heavily on the feature representation of an item v across any user-item (u, v) pair. We strongly affirm this fact because features extracted from product reviews are basically used to describe items and thus the association between items and features appears much more organic and relevant in predicting top recommendation lists and explanation procedures [6, 37]. We can observe this fact naturally stemming from the origin of this form of feature engineering, where in we notice that items are reviewed using certain highlight words and in order to describe any user-item interaction, it would be relevant to utilize these words that are attributed with an item [30]. Hence, we strongly confirm that the item-feature relationships, represented by the Y matrix has a much larger impact in deciding the recommendation lists and the explanations for each user. Hence, it is feasible and discerning to consider improving the robustness of such feature-aware explanation methods from the standpoint of Y. In our proposed framework, we equip the existing framework with a special capability to learn accurate recommendation and explanation procedures when Y is subjected to changes. In Equation 1, we present an adversarial based learning solution that optimizes for the vanilla objective as well as an adversarial objective together. We present the final combined objective as a weighted sum of both the terms using a scalar $\lambda \in (0, 1)$ such that it can determine the penalty imposed on the defense training objective.

$$L_{total}(X, Y \mid \Theta) = (1 - \lambda) \cdot L(X, Y \mid \Theta) + \lambda \cdot L(X, Y + \Delta Y \mid \Theta)$$
(1)

4.2 Defense Capability Limitations in the Adversarial Objective

In order to endow any existing feature-based explainable recommender with resiliency against attacks, we include an additional objective that minimizes the original loss even when *Y* is subject to modifications. However, there are certain limitations in enforcing the modifications to the framework. From Section 3, we can observe that existing item-feature Manuscript submitted to ACM

pairs in the matrix Y are scaled to the range [1, N], where N is the maximum rating of the reviews in the dataset, while scores of those item-feature pairs that do not exist are marked as 0. Another constraint is the magnitude of perturbations introduced for adversarial defense training, such that the performance of the model does not deteriorate on the original data. Thus, we should consider a process of how we induce the modifications to the Y matrix, such that we ensure the model learns defense against the adversarial objective, while constrained by a fixed modification constraint applied to Y. In order to achieve and meet these constraints, we followed Goodfellow et al. [19] in constructing our defense based perturbations ΔY . We used Fast Gradient Sign Method (FGSM) which computes the direction of the gradients of the loss objective while learning. We learn the modification ΔY just like how FGSM based attacks are implemented. We chose to scale our modifications by a global level ϵ_D in such a way that the modifications are constrained within the range $[-\epsilon_D, \epsilon_D]$, as we represent in Equation 2.

$$\Delta Y = \epsilon_D \cdot sign(\Psi) \text{ where } \Psi = \frac{\partial L_{total}(X, Y \mid \Theta)}{\partial Y}$$
(2)

After we learn ΔY , we then ensure that the perturbations don't distort the values of *Y* to a different range outside [0, N]. So, we clipped $Y + \Delta Y$ to a range of [0, N] such that there exists no non-negative component in the modified matrix $Y + \Delta Y$ while the maximum value of this matrix is still *N*, thus obeying the original constraints of *Y*.

4.3 Conceptualizing Adversarial Training to Feature-Aware Explanations

The key motivation behind framing Equations 1 and 2 is derived from the basic learning objective setup by Goodfellow et al. in [19]. However, while the original defense structure is strongly inclined towards computer vision based downstream tasks, we faced certain challenges in providing a qualitative discussion towards elucidating the purpose of including an adversarial objective within this particular domain of feature-aware recommenders. We can simply visualize the qualitative description of the adversarial term in Equation 1, analogous to earlier works that studied defense methods within computer vision tasks [8, 13, 36, 40]. We focus our framework from the single perspective of the Y matrix similar to how adversarial images which are intended to fool the model are constructed by adding FGSM based perturbations into existing original images by retaining the same original label class as the original image. The perturbations added into the Y matrix alter item-feature values in such a way that the item-feature relationships within the $Y + \Delta Y$ matrix may be totally unrepresentative of the original item-feature relationships existent within the dataset. These altered item-feature relationships can possess a direct impact of causing inaccurate learning of the recommendation and explanation procedures of any feature-aware model since we observe that the item-feature relationships is majorly responsible in influencing both recommendation and explanation tasks together. Therefore, it is intuitive to induce perturbations into Y which would be adversarially intended to fool any feature-aware model's joint utilities of recommendation and explainability in order to improve the robustness of explanations of the model. In this case, we chose to learn the perturbations directly from the total objective L_{total} since explainable recommenders learn for a single joint objective that includes both the utilities together. We adhered firmly to the goal of this work which assures that our proposed framework preserves the explainability of the vanilla model under normal conditions as well as retains a large proportion of the explainability when subject to attacks, thus ensuring robust and generalized explanations.

5 WHITE-BOX MODEL PERTURBATION ATTACKS

In order to analyze the vulnerability of our system to external security attacks, we performed a very simple model based attack strategy. We considered the attack setting to be strictly present within the white-box scenario since this would explore the vulnerabilities of the factors responsible for both recommendation and explanation procedures. We leverage an adversarial learning based attack that learns against the true objective of the recommender. We describe the attack as follows:

Constrained Adversarial Attack: We can optimize for the original model parameters as per Equation 3:

$$\hat{\Theta} = \arg\min_{\Theta} L_{total}(D : X, Y \mid \Theta)$$
(3)

The adversarial attack Δ which is introduced into the model weights, is learnt in such a way we constrain the attack by a global level ϵ_A^{-1} . We learn Δ against the original model's objective directly as described in Equation 4.

$$\Delta^* = \arg\max_{\Delta} L_{total}(D; \hat{\Theta} + \Delta) \text{ such that } \|\Delta\| \le \epsilon_A \tag{4}$$

However, we observe that we cannot obtain the optimal exact solution directly for Equation 4 since it is intractable to directly optimize for constrained maximization. Therefore, we followed [3, 22, 52, 53] to optimize the maximization using the value of the normalized model weight's gradient of the total loss, which is inspired by the FGSM method [19]. We describe this optimization technique in Equation 5.

$$\Delta^* = \epsilon_A \frac{\Xi}{\|\Xi\|} \text{ where } \Xi = \frac{\partial L_{total}(D; \hat{\Theta} + \Delta)}{\partial \Delta}$$
(5)

Finally, we introduce Δ^* into the original model parameters to attack the original model and hence observe the explainability under these conditions. For performing our attacks, we chose to attack all the weight parameters of each model.

6 EXPERIMENTAL DESIGN

6.1 Datasets

For our experiments, we chose datasets of different scales from popular E-commerce systems: $Yelp^2$ and Amazon³. Yelp dataset contains reviews of restaurants, hospitals, salons, hotels, travel agencies across the world. There are many subsets of the Amazon review datasets, amongst which we chose CDs and Vinyl (about CD sales; referred CD everywhere else), and Kindle (about Kindle store sales).

Preprocessing: We removed users with lesser than 20 reviews for the Yelp dataset and lesser than 10 reviews for the Amazon datasets in order to improve the density of the datasets. We created the testing set as follows: for each user, we keep the last 6 interacted (positive) items by time and randomly sample 100 (negative) items that are not interacted by the user. We formed the validation data by choosing the latest (by time) interacted positive item and 10 random negative items for each user. We present our dataset statistics in Table 1.

 $^{^1\|\}cdot\|$ refers to the L2-norm

²https://www.yelp.com/dataset.

³https://nijianmo.github.io/amazon/index.html.

Manuscript submitted to ACM

Dataset	Users	Items	Features	Reviews	Sparsity(%)
Kindle	5,907	41,402	77	136,039	0.05563
CD	8,119	52,193	230	245,391	0.05791
Yelp	12,163	20,256	107	510,396	0.2072

Table 1. Dataset Statistics

6.2 Explainable RS Methods

In order to validate the efficiency of our framework in robustifying explanations, we chose two popular SOTA featureaware explainable recommenders which possess different architectural structures and learning objectives for both explanation and recommendation. We describe the methods as follows:

- **CER: Counterfactual Explainable Recommendation** [47]: A neural network model comprised of two hidden layers with *X* and *Y* as inputs is the main recommender, which predicts the matching score for each user-item pair. The explanation procedure is learnt separate as a counterfactual module that learns the most minimal changes applied on the item feature space for all the top *K* recommendations of a user, so that the item is no longer recommended to the user.
- EFM: Explicit Factor Modeling [55]: This is a factorization based model, which reconstructs the inputs: user-item interaction matrix *A*, user-feature matrix *X*, and item-feature matrix *Y* by decomposing each matrix into smaller rank non-negative matrices. We added an additional non negative loss term that penalizes the negative weights in order to optimize for non-negative weights using gradient descent. The explanation for each user-item pair is constructed by picking the best scoring feature in reconstructed *Y* vector for the item amongst the top scoring features within the reconstructed *X* for that user.

6.3 Evaluation Metrics

For evaluating recommendation utility, we used the standard ranking measure: Normalized Discounted Cumulative Gain (NDCG). We evaluated the accuracy and relevance of the explanations as suggested by [46, 47, 51, 57]. We compared the efficiency of the generated explanations with the gold truth of those features found in the reviews of any user-item interaction, which have been mentioned with positive sentiment. We used three standard metrics for these feature comparison tasks: Feature-level Precision, Recall, and F1 (harmonic mean of Precision and Recall) scores of the explanations and we report the average metric scores across explained samples for which a review actually exists⁴. We denote the metrics as Expl Pr, Expl Re and Expl F1 respectively.

6.4 Training and Evaluation Settings

6.4.1 Training Setting. For conducting our experiments, we trained all the vanilla and defense models until convergence and we set batch size as 32. We optimized all the models using Adam optimizer [28]. We performed hyper-parameter tuning using validation data for the weight decay and learning rate selecting them from the range $\{1e^{-5}, 1e^{-4}, 0.001, 0.01, 0.05, 0.1, 0.5\}$. The attack versions of all the models are trained in the same conditions as their

⁴Yelp dataset offers at most one feature,opinion,sentiment triplet extracted by the Sentires tool per each review. Thus, Feature-level Precision and Recall values would be identical for all Yelp experiments.

base models, with ϵ_A chosen within the [0, 1] range. We set each model's hyperparameters as suggested in their original works.

6.4.2 Evaluation Setting. We followed a simple evaluation strategy by explaining all the top K = 5 recommendations per every user for the vanilla model. Then, we form a collection of all the positive items that were correctly recommended in each user's top K = 5 suggestions during the vanilla model task as the standard comparison test bed for each algorithm-dataset combination. We evaluate all the attack and defense models on this fixed evaluation set in order to facilitate our comparison analyses. In addition, we also perform masking which selects explanations only from the features mentioned by that particular user.

7 RESULTS

We visualize our results using Figures 1 and 2 regarding the study on ϵ_D and via Tables 2, 3 and 4 regarding the impact of λ . From the experiments conducted, we can notice that our framework does empirically present an improvement in the explainability of the model under attack for almost all the cases. The robustness improvement is visible in all the CER and EFM-based models, particularly more within the former. We remark that we experience a slight drop in the explainability in CER models across the clean (non-attacked) model trained under the defense framework when compared to the vanilla model. However, since we desired to endue explanations with resilience to adversarial attacks, we are willing to accept a slight drop in the clean explainability which comes at a cost of including the defense training. We also notice there is a much better generalization of explainability within the EFM models, with the clean performance of models when trained under our defense framework being at times better than the clean performance of the original vanilla EFM models. In Subsection 7.1, we will discuss the impact of magnitude of the perturbations introduced during defense training (ϵ_D), and in Subsection 7.2, we discuss the impact of loss scale penalty (λ) applied on the defense objective while regularizing the training objective.

7.1 Impact of ϵ_D

7.1.1 Behavior of Neural Network based explainable RS. In CER models, we can observe that this model is highly sensitive towards larger perturbations mainly because neural network based models are very sensitive towards large magnitude perturbations [4, 34, 43]. In Figures 1(a), 1(b) and 1(c), we can clearly see that larger ϵ_D plots such as the green ($\epsilon_D = 0.75$) and red ($\epsilon_D = 1$) plots lead to poorer robustness performance, in fact worse than the vanilla due to the increasing magnitude of perturbations induced into the input (especially $\epsilon_D = 1$ for Yelp in Figure 1(a) which just collapses). Therefore, we can deduce that large distortion in the input can cause deterioration of the model's performance on the original data. In Figure 1(a), we can similarly observe some of the larger ϵ_D plots are non-monotonic, confirming the fact that larger distortions lead to unstable recommendation efficiency and inconsistent explainability when trained on the Yelp (densest) dataset.

However, the blue ($\epsilon_D = 0.25$) plots lead to much smoother curves in all datasets, implying explanations are indeed more robust under smaller ϵ_D as ϵ_A increases. We can observe this behavior more strikingly within the CD dataset, which has the densest Y and thus depicts the largest impact. In Figure 1(b), the explainability of the defense model ($\epsilon_D = 0.25$ blue plot) is much more accurate than the vanilla model at $\epsilon_A = 1$. We can see a very similar trend even across smaller datasets such as Kindle. In Figure 1(c), $\epsilon_D = 0.25$ and $\epsilon_D = 0.5$ plots perform better than vanilla at $\epsilon_A = 1$ Manuscript submitted to ACM



Fig. 1. Robustness performance of the explainability by comparing the vanilla model and defense variants of neural network-based CER models. The X-axis is the noise level ϵ_A and the Y-axis is Explainability F1 score. The black plots correspond to the Vanilla and colored plots represent different ϵ_D for fixed $\lambda = 0.5$: Blue ($\epsilon_D = 0.25$), Orange ($\epsilon_D = 0.5$), Green ($\epsilon_D = 0.75$) and Red ($\epsilon_D = 1$). The best performing ϵ_D is identified based on how close is the clean performance of the explainability (top-left point of each color plot) when compared to the clean performance under the vanilla conditions (top-left point of the black plot) and also how less and consistent is the explainability drop under increasing ϵ_A levels (the flatness of the color plots).

in the Kindle dataset. This implies that CER models, when trained using our framework with smaller ϵ_D can preserve the explainability when subject to external attack conditions.

In addition to ensuring robustness of explanations under attack conditions, we can observe that CER models when trained with our framework under smaller ϵ_D can yield a clean explainability performance that is comparable (although slightly lesser) to the clean performance of the vanilla model. This property can be visually observed based on the closeness between the starting top-left points of each color plot and the top-left point of the black plot in Figures 1(a), 1(b) and 1(c). Therefore, our framework is capable of ensuring that CER models generalize well by producing clean explainability performance that is very similar to the vanilla model's clean performance. From these results, we directly deduce that our framework is able to generate explanations that are trustworthy and not expected to change under attack. Such trustworthy explanations that are resilient to external attacks indicate a correct identification of the underlying true features/reasons contributing to the outcome.

Thus we remark that the magnitude of perturbations applied to *Y* must be carefully considered for larger datasets (mainly CD and Yelp) while incorporating defense mechanisms, since it may drastically change the original relationship between the inputs and the observed outcomes and cause inconsistent explanation behavior as a consequence. However, we can ensure that the robustness of explanations provided by neural network recommenders can be improved majorly using our framework using smaller ϵ_D .

7.1.2 Behavior of Factorization based explainable RS. In general, EFM models are less vulnerable to attacks than CER models in almost all the datasets mainly because factorization models typically show lesser sensitivity than neural network models. However, there is a visible improvement in reducing the drop of explainability under large ϵ_A when compared to vanilla in almost all the cases, implying more robustness in the explanations. In EFM based models, we observe a trend that the robustness in explanations is improved with smaller values of ϵ_D as the scale of the dataset increases. In particular, we can notice that smaller ϵ_D leads to smaller perturbations and thus much more refined improvement in the explanations under attack in denser datasets: Yelp and CD (see $\epsilon_D = 0.25$ blue plot in Figure 2(a) Manuscript submitted to ACM



Fig. 2. Robustness performance of the explainability by comparing the vanilla model and defense variants of factorization-based EFM models. The X-axis is the noise level ϵ_A and the Y-axis is Explainability F1 score. The black plots correspond to the Vanilla and colored plots represent different ϵ_D for fixed $\lambda = 0.5$: Blue ($\epsilon_D = 0.25$), Orange ($\epsilon_D = 0.5$), Green ($\epsilon_D = 0.75$) and Red ($\epsilon_D = 1$). The best performing ϵ_D is identified based on how close is the clean performance of the explainability (top-left point of each color plot) when compared to the clean performance under the vanilla conditions (top-left point of the black plot) and also how less and consistent is the explainability drop under increasing ϵ_A levels (the flatness of the color plots).

and $\epsilon_D = 0.5$ orange plot in Figure 2(b)) while larger ϵ_D models display more sustenance within smaller datasets such as Kindle (see Figure 2(c), especially $\epsilon_D = 0.75$ green plot). The main reason for this observation is because factorization based models increase in model size as the dataset scale increases. Therefore, increasing magnitude of perturbations bear an increasing impact in skewing the reconstruction learning process followed by these models. This effect would be magnified more in larger size models which would result in rendering the model less effective in improving the robustness of explanations under increasing attack levels. Therefore we can notice that smaller ϵ_D for larger datasets and larger ϵ_D for smaller datasets improves robustness for EFM models.

Another interesting facet of discussion would be regarding the generalization of explainability. Within EFM models, we can observe that the clean performance of the defense version is typically better than the clean performance of the vanilla version, particularly for both Yelp and CD (see higher top-left starting points for some defense plots than the vanilla's starting point in Figures 2(a) and 2(b)). We attribute the improvement in the generalization due to our framework's incorporation of the defense loss term in Equation 1 which allows regularization of the reconstruction term of Y when subject to modifications in the true loss objective. Thus, this improves the efficiency of the reconstruction process and we can obtain better quality of explanations. Therefore, factorization based recommenders trained with our framework generalize explanations better while also displaying increased robustness in explainability under attack conditions.

7.2 Impact of λ

From our results, we can observe that λ is another sensitive hyper-parameter that needs to be chosen carefully when we train models with our framework. We find that larger defense objective weight (λ) values results in lesser robustness. Similar to the discussion about ϵ_D in Subsection 7.1, we can again observe that CER models display more sensitivity towards increasing λ in larger datasets. We can notice in Tables 2 and 3 where CER models display poorer performance of explanations under attack, especially when trained with larger λ values. Infact, $\lambda = 0.9$ reports worse explanation Manuscript submitted to ACM Robust Explainable Recommendation

Table 2. Performance of our defense variants for both CER and EFM models when trained with different λ on Yelp. We chose the best ϵ_D as obtained from Figures 1 and 2. The bold values represent the results of the best λ that can redeem most of the clean vanilla's explainability and experiences the least drop from the clean performance when subject to attack conditions.

	Loss scale (λ)	Clean without Attack				FGSM Attack with $\epsilon_A = 1$				
CER with $\epsilon_D = 0.5$	Loss scale (it)	NDCG@100	Expl Pr	Expl Re	Expl F1	NDCG@100	Expl Pr	Expl Re	Expl F1	
	0 (Vanilla)	0.50413	0.06330	0.06330	0.06330	0.43657	0.01543	0.01543	0.01543	
	0.01	0.50557	0.04698	0.04698	0.04698	0.32628	0.01057	0.01057	0.01057	
	0.05	0.50551	0.05342	0.05342	0.05342	0.32630	0.01054	0.01054	0.01054	
	0.1	0.50532	0.04815	0.04815	0.04815	0.32638	0.01007	0.01007	0.01007	
	0.5	0.49958	0.05592	0.05592	0.05592	0.49360	0.03239	0.03239	0.03239	
	0.9	0.38017	0.01002	0.01002	0.01002	0.38017	0.01002	0.01002	0.01002	
	Loss scale (λ)	Clea	an withou	ıt Attack		FGSM	I Attack v	with $\epsilon_A =$	1	
	Loss scale (λ)	Clea NDCG@100	an withou Expl Pr	ıt Attack Expl Re	Expl F1	FGSM NDCG@100	l Attack v Expl Pr	with $\epsilon_A =$ Expl Re	1 Expl F1	
	Loss scale (λ) 0 (Vanilla)	Clea NDCG@100 0.65337	an withou Expl Pr 0.05663	it Attack Expl Re 0.05663	Expl F1 0.05663	FGSM NDCG@100 0.26988	Attack v Expl Pr 0.02832	with $\epsilon_A =$ Expl Re 0.02832	1 Expl F1 0.02832	
	Loss scale (λ) 0 (Vanilla) 0.01	Clea NDCG@100 0.65337 0.74258	an withou Expl Pr 0.05663 0.05777	Expl Re 0.05663 0.05777	Expl F1 0.05663 0.05777	FGSM NDCG@100 0.26988 0.51526	I Attack v Expl Pr 0.02832 0.02994	with $\epsilon_A =$ Expl Re 0.02832 0.02994	1 Expl F1 0.02832 0.02994	
EFM with $\epsilon_D = 0.25$	Loss scale (λ) 0 (Vanilla) 0.01 0.05	Clea NDCG@100 0.65337 0.74258 0.70613	an withou Expl Pr 0.05663 0.05777 0.06028	Attack Expl Re 0.05663 0.05777 0.06028	Expl F1 0.05663 0.05777 0.06028	FGSM NDCG@100 0.26988 0.51526 0.81974	Attack v Expl Pr 0.02832 0.02994 0.02063	with $\epsilon_A =$ Expl Re 0.02832 0.02994 0.02063	1 Expl F1 0.02832 0.02994 0.02063	
EFM with $\epsilon_D = 0.25$	Loss scale (λ) 0 (Vanilla) 0.01 0.05 0.1	Cle: NDCG@100 0.65337 0.74258 0.70613 0.70443	an withou Expl Pr 0.05663 0.05777 0.06028 0.05906	Attack Expl Re 0.05663 0.05777 0.06028 0.05906	Expl F1 0.05663 0.05777 0.06028 0.05906	FGSM NDCG@100 0.26988 0.51526 0.81974 0.30785	Attack v Expl Pr 0.02832 0.02994 0.02063 0.03188	with $\epsilon_A =$ Expl Re 0.02832 0.02994 0.02063 0.03188	1 Expl F1 0.02832 0.02994 0.02063 0.03188	
EFM with $\epsilon_D = 0.25$	Loss scale (λ) 0 (Vanilla) 0.01 0.05 0.1 0.5	Cle: NDCG@100 0.65337 0.74258 0.70613 0.70443 0.72644	an withou Expl Pr 0.05663 0.05777 0.06028 0.05906 0.05922	Attack Expl Re 0.05663 0.05777 0.06028 0.05906 0.05922	Expl F1 0.05663 0.05777 0.06028 0.05906 0.05922	FGSM NDCG@100 0.26988 0.51526 0.81974 0.30785 0.46621	Attack v Expl Pr 0.02832 0.02994 0.02063 0.03188 0.03592	vith $\epsilon_A =$ Expl Re 0.02832 0.02994 0.02063 0.03188 0.03592	Expl F1 0.02832 0.02994 0.02063 0.03188 0.03592	

Table 3. Performance of our defense variants for both CER and EFM models when trained with different λ on CD. We chose the best ϵ_D as obtained from Figures 1 and 2. The bold values represent the results of the best λ that can redeem most of the clean vanilla's explainability and experiences the least drop from the clean performance when subject to attack conditions.

	\mathbf{I}_{OSS} scale (3)	Clean without Attack				FGSM Attack with $\epsilon_A = 1$			
CER with $\epsilon_D = 0.25$	Loss scale (it)	NDCG@100	Expl Pr	Expl Re	Expl F1	NDCG@100	Expl Pr	Expl Re	Expl F1
	0 (Vanilla)	0.54830	0.25284	0.16329	0.18673	0.39752	0.00000	0.00000	0.00000
	0.01	0.55450	0.19624	0.12669	0.14497	0.51179	0.16832	0.10990	0.12542
	0.05	0.55476	0.18985	0.12063	0.13873	0.47100	0.05861	0.03913	0.04452
	0.1	0.54766	0.18730	0.11866	0.13666	0.33380	0.03883	0.02656	0.02983
	0.5	0.58279	0.24907	0.16255	0.18528	0.4834	0.20183	0.13039	0.14938
	0.9	0.57579	0.24649	0.15597	0.17919	0.31812	0.03485	0.02396	0.02689
	Loss scale (λ)	Cle	an withou	ıt Attack		FGSM	I Attack v	with $\epsilon_A =$	1
	Loss scale (λ)	Clea NDCG@100	an withou Expl Pr	ıt Attack Expl Re	Expl F1	FGSM NDCG@100	l Attack v Expl Pr	with ϵ_A = Expl Re	1 Expl F1
	Loss scale (λ) 0 (Vanilla)	Cle: NDCG@100 0.28809	an withou Expl Pr 0.31935	It Attack Expl Re 0.20439	Expl F1 0.23472	FGSM NDCG@100 0.36683	Attack v Expl Pr 0.16057	with $\epsilon_A =$ Expl Re 0.0987	1 Expl F1 0.11446
	Loss scale (λ) 0 (Vanilla) 0.01	Cle: NDCG@100 0.28809 0.36021	an withou Expl Pr 0.31935 0.30056	It Attack Expl Re 0.20439 0.19107	Expl F1 0.23472 0.21974	FGSM NDCG@100 0.36683 0.39460	I Attack v Expl Pr 0.16057 0.24677	with $\epsilon_A =$ Expl Re 0.0987 0.15577	1 Expl F1 0.11446 0.17950
EFM with $\epsilon_D = 0.5$	Loss scale (λ) 0 (Vanilla) 0.01 0.05	Cle: NDCG@100 0.28809 0.36021 0.26817	an withou Expl Pr 0.31935 0.30056 0.30759	It Attack Expl Re 0.20439 0.19107 0.19525	Expl F1 0.23472 0.21974 0.22473	FGSM NDCG@100 0.36683 0.39460 0.34845	Attack v Expl Pr 0.16057 0.24677 0.25701	with $\epsilon_A =$ Expl Re 0.0987 0.15577 0.16215	1 Expl F1 0.11446 0.17950 0.18703
EFM with $\epsilon_D = 0.5$	Loss scale (λ) 0 (Vanilla) 0.01 0.05 0.1	Cle: NDCG@100 0.28809 0.36021 0.26817 0.38964	an withou Expl Pr 0.31935 0.30056 0.30759 0.31276	Attack Expl Re 0.20439 0.19107 0.19525 0.19772	Expl F1 0.23472 0.21974 0.22473 0.22796	FGSM NDCG@100 0.36683 0.39460 0.34845 0.49462	Attack v Expl Pr 0.16057 0.24677 0.25701 0.26877	with $\epsilon_A =$ Expl Re 0.0987 0.15577 0.16215 0.17054	1 Expl F1 0.11446 0.17950 0.18703 0.19619
EFM with $\epsilon_D = 0.5$	Loss scale (λ) 0 (Vanilla) 0.01 0.05 0.1 0.5	Cle: NDCG@100 0.28809 0.36021 0.26817 0.38964 0.36705	an withou Expl Pr 0.31935 0.30056 0.30759 0.31276 0.32104	It Attack Expl Re 0.20439 0.19107 0.19525 0.19772 0.20412	Expl F1 0.23472 0.21974 0.22473 0.22796 0.23492	FGSM NDCG@100 0.36683 0.39460 0.34845 0.49462 0.59024	Attack v Expl Pr 0.16057 0.24677 0.25701 0.26877 0.24686	with $\epsilon_A =$ Expl Re 0.0987 0.15577 0.16215 0.17054 0.15908	1 Expl F1 0.11446 0.17950 0.18703 0.19619 0.18226

performance than vanilla under attack for the Yelp dataset. Similarly, EFM-based models display a decrease in the robustness as we increase λ . We observe this behavior in both these type of models because our framework regularizes the models to learn the utility more as per the adversarially perturbed *Y* matrix resulting in emphasizing more learning according to the wronger input pattern and thus resulting in weaker explanations.

	Loss scale (λ)	Clean without Attack				FGSM Attack with $\epsilon_A = 1$				
CER with $\epsilon_D = 0.5$	Loss scale (it)	NDCG@100	Expl Pr	Expl Re	Expl F1	NDCG@100	Expl Pr	Expl Re	Expl F1	
	0 (Vanilla)	0.45278	0.43332	0.34505	0.37167	0.37154	0.01904	0.01453	0.01589	
	0.01	0.45811	0.36913	0.28953	0.31339	0.36298	0.09018	0.06630	0.07327	
	0.05	0.45745	0.37175	0.29198	0.31587	0.36118	0.09255	0.06722	0.07461	
	0.1	0.45661	0.36995	0.29105	0.31475	0.36095	0.10213	0.07089	0.07983	
	0.5	0.44900	0.42518	0.33854	0.36468	0.37229	0.12066	0.09021	0.09937	
	0.9	0.43982	0.42539	0.33713	0.36362	0.37787	0.01258	0.10283	0.01099	
	Loss scale (λ)	Clea	n without Attack			FGSM Attack with $\epsilon_A = 1$				
EFM with $\epsilon_D = 0.75$	2000 00010 (//)	NDCG@100	Expl Pr	Expl Re	Expl F1	NDCG@100	Expl Pr	Expl Re	Expl F1	
	0 (Vanilla)	0.30919	0.41572	0.33086	0.35650	0.36318	0.30535	0.24413	0.26255	
	0.01	0 30884	0.40671	0 3 2 1 0 3	0.24(77	0.07501	0 40 40 9	0.01000	0.04500	
		0.50001	0.40071	0.52105	0.54677	0.3/531	0.40498	0.31939	0.34509	
EFM with $\epsilon_D = 0.75$	0.05	0.23504	0.40649	0.32103	0.34677	0.37531	0.40498	0.31939	0.34509	
EFM with $\epsilon_D = 0.75$	0.05	0.23504 0.25977	0.40649 0.40649	0.32093 0.32093	0.34663 0.34663	0.37531 0.33649 0.35695	0.40498 0.40455 0.40477	0.31939 0.31951 0.31932	0.34509 0.34508 0.34498	
EFM with $\epsilon_D = 0.75$	0.05 0.1 0.5	0.23504 0.25977 0.31252	0.40649 0.40649 0.40971	0.32103 0.32093 0.32093 0.32457	0.34677 0.34663 0.34663 0.35025	0.37531 0.33649 0.35695 0.38617	0.40498 0.40455 0.40477 0.40090	0.31939 0.31951 0.31932 0.31982	0.34509 0.34508 0.34498 0.34424	

Table 4. Performance of our defense variants for both CER and EFM models when trained with different λ on Kindle. We chose the best ϵ_D as obtained from Figures 1 and 2. The bold values represent the results of the best λ that can redeem most of the clean vanilla's explainability and experiences the least drop from the clean performance when subject to attack conditions.

However, larger λ typically results in better generalization and a much closer clean performance of the defense model in comparison to the clean performance provided by the vanilla models. In fact, we can observe that EFM models at times generalize much better (Tables 2 and 3 display a higher clean performance than their vanilla) mainly because of the improved factorization ensured via regularizing the defense objective. This leads to decide between a trade-off between the generalization and robustness of the generated explanations while selecting λ . For example in Tables 3 and 4, we can observe a slight (though not strict) upward trend in the clean performance for both the models as we increase λ , but however the explainability under attack keeps deteriorating indicating weaker robustness.

We can also observe that smaller values of λ are not effective in endowing robustness to the explanations, due to its small penalty applied on the defense loss. For example, in Table 2, we can see that for both CER and EFM models, the explainability under attack does not improve largely against the attack explainability of the vanilla for $\lambda = 0.01, 0.05$. We can also observe that smaller λ does not contribute in improving the clean performance of the model as compared to the vanilla and it offers weaker generalization of the explanations. In Table 3, we can notice that CER models present a visible drop in the clean explainability for $\lambda = 0.01, 0.05$ as compared to the clean performance of the vanilla.

Additionally, we also remark that when both the models are trained on the Kindle dataset (see Table 4), we observe minimal improvements in the robustness as well as the generalization of the explanations. We observe this behavior because of the small rank of *Y* in the Kindle dataset (due the least number of features amongst the other datasets), which thus depicts minimal impact as we change λ . Therefore, λ does not bear a huge influence across small scale datasets.

In almost all the experiments, we can observe that λ values that do not allow a disproportionate weightage on either of the objectives, such as 0.5 report better generalization and robustness together thus leading to much better performance for clean and attack conditions. In fact, when $\lambda = 0.5$, we apply an equal weightage to both the terms, Manuscript submitted to ACM which allows improvement to the explanation robustness and generalization of the model. Thus, we can infer that λ values which balances the learning of the model according to the original and the perturbed data, should be chosen in consideration to the amount of robustness of the explanations we want to gain.

8 CONCLUSION & FUTURE WORK

In this work, we introduce a framework for feature-aware explainable recommenders that supports extensibility and adaptability to all similar recommenders that follow the same style and pattern of learning objectives with which we construct our framework. Our main aim was to improve the robustness as well as the generalization of the explanations overall, thus enhancing the overall quality of feature-aware user personalized explanations in RS. From our results, we deduce that the improvements are uniform across all the datasets for both the algorithms, thus empirically providing a much more reliable platform for enhancing the trustworthiness of explanations in RS. Neural network based CER models display larger increased robustness of the true explanations provided under attack circumstances, whenever trained with small modifications to the input. Although we notice a small drop in the clean explainability within CER models generalize much better due to its factorization based learning objective, allowing much better capturing of the true reasons contributing to the recommendation outcomes. Thus, we can conclude that the explainability of factorization based models can be generalized better while the explainability of neural network based models can be stabilized better with our framework.

However, we identify some limitations to our study. While we have only considered the generalization and robustness of explanations, we remark that our framework could have considered modeling other aspects of explainability additionally, such as the fairness of the explanations [16]. Finally, we conclude stating that our framework is instrumental in providing an adaptable framework for feature-aware RS which is an early work in developing more robust explainable RS, while also accounting for generalization of the global-level explainability. We identify a significant field of study within explainable RS, which would allow fresher paradigm of robust and generalized explanations within RS.

ACKNOWLEDGMENTS

We would like to acknowledge the valuable discussions and suggestions provided from time to time by Vipin Pillai.

Sairamvinay Vijayaraghavan and Prasant Mohapatra

REFERENCES

- Julius Adebayo, Justin Gilmer, Michael Muelly, Ian Goodfellow, Moritz Hardt, and Been Kim. 2020. Sanity Checks for Saliency Maps. arXiv:1810.03292 [cs.CV]
- [2] David Alvarez-Melis and Tommi S. Jaakkola. 2018. On the Robustness of Interpretability Methods. http://arxiv.org/abs/1806.08049 arXiv:1806.08049
 [cs, stat].
- [3] Vito Walter Anelli, Alejandro Bellogín, Yashar Deldjoo, Tommaso Di Noia, and Felice Antonio Merra. 2020. Multi-Step Adversarial Perturbations on Recommender Systems Embeddings. http://arxiv.org/abs/2010.01329 arXiv:2010.01329 [cs].
- [4] Ali Borji and Sikun Lin. 2019. White Noise Analysis of Neural Networks. arXiv:1912.12106 [cs.CV]
- [5] Chao Chen, Chenghua Guo, Guixiang Ma, Ming Zeng, Xi Zhang, and Sihong Xie. 2023. Robust Ranking Explanations. arXiv:2307.04024 [cs.LG]
- [6] Li Chen and Feng Wang. 2017. Explaining Recommendations Based on Feature Sentiments in Product Reviews. In Proceedings of the 22nd International Conference on Intelligent User Interfaces (Limassol, Cyprus) (IUI '17). Association for Computing Machinery, New York, NY, USA, 17–28. https://doi.org/10.1145/3025171.3025173
- [7] Tong Chen, Hongzhi Yin, Guanhua Ye, Zi Huang, Yang Wang, and Meng Wang. 2020. Try This Instead: Personalized and Interpretable Substitute Recommendation. In Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval. ACM, Virtual Event China, 891–900. https://doi.org/10.1145/3397271.3401042
- [8] Xu Chen, Chuancai Liu, Yue Zhao, Zhiyang Jia, and Ge Jin. 2022. Improving adversarial robustness of Bayesian neural networks via multi-task adversarial training. Information Sciences 592 (May 2022), 156–173. https://doi.org/10.1016/j.ins.2022.01.051
- [9] Zhiyong Cheng, Ying Ding, Xiangnan He, Lei Zhu, Xuemeng Song, and Mohan Kankanhalli. 2018. A^3NCF: An Adaptive Aspect Attention Model for Rating Prediction. In Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence. International Joint Conferences on Artificial Intelligence Organization, Stockholm, Sweden, 3748–3754. https://doi.org/10.24963/ijcai.2018/521
- [10] Felipe Costa, Sixun Ouyang, Peter Dolog, and Aonghus Lawlor. 2018. Automatic Generation of Natural Language Explanations. In Proceedings of the 23rd International Conference on Intelligent User Interfaces Companion. ACM, Tokyo Japan, 1–2. https://doi.org/10.1145/3180308.3180366
- [11] Ronky Francis Doh, Conghua Zhou, John Kingsley Arthur, Isaac Tawiah, and Benjamin Doh. 2022. A Systematic Review of Deep Knowledge Graph-Based Recommender Systems, with Focus on Explainable Embeddings. Data 7, 7 (July 2022), 94. https://doi.org/10.3390/data7070094
- [12] Ann-Kathrin Dombrowski, Maximilian Alber, Christopher J. Anders, Marcel Ackermann, Klaus-Robert Müller, and Pan Kessel. 2019. Explanations can be manipulated and geometry is to blame. http://arxiv.org/abs/1906.07983 arXiv:1906.07983 [cs, stat].
- [13] Yinpeng Dong, Hang Su, Jun Zhu, and Fan Bao. 2017. Towards Interpretable Deep Neural Networks by Leveraging Adversarial Examples. http://arxiv.org/abs/1708.05493 arXiv:1708.05493 [cs].
- [14] Christian Etmann, Sebastian Lunz, Peter Maass, and Carola-Bibiane Schönlieb. 2019. On the Connection Between Adversarial Robustness and Saliency Map Interpretability. http://arxiv.org/abs/1905.04172 arXiv:1905.04172 [cs, stat].
- [15] Wenqi Fan, Han Xu, Wei Jin, Xiaorui Liu, Xianfeng Tang, Suhang Wang, Qing Li, Jiliang Tang, Jianping Wang, and Charu Aggarwal. 2023. Jointly Attacking Graph Neural Network and its Explanations. In 2023 IEEE 39th International Conference on Data Engineering (ICDE). IEEE, Anaheim, CA, USA, 654–667. https://doi.org/10.1109/ICDE55515.2023.00056
- [16] Zuohui Fu, Yikun Xian, Ruoyuan Gao, Jieyu Zhao, Qiaoying Huang, Yingqiang Ge, Shuyuan Xu, Shijie Geng, Chirag Shah, Yongfeng Zhang, and Gerard de Melo. 2020. Fairness-Aware Explainable Recommendation over Knowledge Graphs. http://arxiv.org/abs/2006.02046 arXiv:2006.02046 [cs].
- [17] Yingqiang Ge, Shuchang Liu, Zuohui Fu, Juntao Tan, Zelong Li, Shuyuan Xu, Yunqi Li, Yikun Xian, and Yongfeng Zhang. 2022. A survey on trustworthy recommender systems. arXiv preprint arXiv:2207.12515 (2022).
- [18] Yingqiang Ge, Juntao Tan, Yan Zhu, Yinglong Xia, Jiebo Luo, Shuchang Liu, Zuohui Fu, Shijie Geng, Zelong Li, and Yongfeng Zhang. 2022. Explainable Fairness in Recommendation. In Proceedings of the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval. ACM, Madrid Spain, 681–691. https://doi.org/10.1145/3477495.3531973
- [19] Ian J. Goodfellow, Jonathon Shlens, and Christian Szegedy. 2014. Explaining and Harnessing Adversarial Examples. (2014). https://doi.org/10.48550/ ARXIV.1412.6572 Publisher: arXiv Version Number: 3.
- [20] Xinyu Guan, Zhiyong Cheng, Xiangnan He, Yongfeng Zhang, Zhibo Zhu, Qinke Peng, and Tat-Seng Chua. 2019. Attentive Aspect Modeling for Review-Aware Recommendation. ACM Transactions on Information Systems 37, 3 (July 2019), 1–27. https://doi.org/10.1145/3309546
- [21] Leif Hancox-Li. 2020. Robustness in machine learning explanations: does it matter?. In Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency. ACM, Barcelona Spain, 640–647. https://doi.org/10.1145/3351095.3372836
- [22] 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 & Development in Information Retrieval*. 355–364. https://doi.org/10.1145/3209978.3209981 arXiv:1808.03908 [cs, stat].
- [23] Juyeon Heo, Sunghwan Joo, and Taesup Moon. 2019. Fooling Neural Network Interpretations via Adversarial Model Manipulation. http: //arxiv.org/abs/1902.02041 arXiv:1902.02041 [cs, stat].
- [24] Yunfeng Hou, Ning Yang, Yi Wu, and Philip S. Yu. 2019. Explainable recommendation with fusion of aspect information. World Wide Web 22, 1 (Jan. 2019), 221–240. https://doi.org/10.1007/s11280-018-0558-1

Manuscript submitted to ACM

14

Robust Explainable Recommendation

- [25] Chao Huang, Huance Xu, Yong Xu, Peng Dai, Lianghao Xia, Mengyin Lu, Liefeng Bo, Hao Xing, Xiaoping Lai, and Yanfang Ye. 2021. Knowledge-aware Coupled Graph Neural Network for Social Recommendation. Proceedings of the AAAI Conference on Artificial Intelligence 35, 5 (May 2021), 4115–4122. https://doi.org/10.1609/aaai.v35i5.16533
- [26] Beomsu Kim, Junghoon Seo, and Taegyun Jeon. 2019. Bridging Adversarial Robustness and Gradient Interpretability. http://arxiv.org/abs/1903.11626 arXiv:1903.11626 [cs, stat].
- [27] Pieter-Jan Kindermans, Sara Hooker, Julius Adebayo, Maximilian Alber, Kristof T. Schütt, Sven Dähne, Dumitru Erhan, and Been Kim. 2017. The (Un)reliability of saliency methods. http://arxiv.org/abs/1711.00867 arXiv:1711.00867 [cs, stat].
- [28] Diederik P. Kingma and Jimmy Ba. 2017. Adam: A Method for Stochastic Optimization. arXiv:1412.6980 [cs.LG]
- [29] Himabindu Lakkaraju, Nino Arsov, and Osbert Bastani. 2020. Robust and Stable Black Box Explanations. arXiv:2011.06169 [cs.LG]
- [30] Trung-Hoang Le and Hady W. Lauw. 2021. Explainable Recommendation with Comparative Constraints on Product Aspects. In Proceedings of the 14th ACM International Conference on Web Search and Data Mining. ACM, Virtual Event Israel, 967–975. https://doi.org/10.1145/3437963.3441754
- [31] Lei Li, Yongfeng Zhang, and Li Chen. 2021. Personalized Transformer for Explainable Recommendation. http://arxiv.org/abs/2105.11601 arXiv:2105.11601 [cs].
- [32] Piji Li, Zihao Wang, Zhaochun Ren, Lidong Bing, and Wai Lam. 2017. Neural Rating Regression with Abstractive Tips Generation for Recommendation. In Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval. ACM, Shinjuku Tokyo Japan, 345–354. https://doi.org/10.1145/3077136.3080822
- [33] Dohun Lim, Hyeonseok Lee, and Sungchan Kim. 2021. Building Reliable Explanations of Unreliable Neural Networks: Locally Smoothing Perspective of Model Interpretation. In 2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). IEEE, Nashville, TN, USA, 6464–6473. https://doi.org/10.1109/CVPR46437.2021.00640
- [34] Mengchen Liu, Shixia Liu, Hang Su, Kelei Cao, and Jun Zhu. 2018. Analyzing the Noise Robustness of Deep Neural Networks. arXiv:1810.03913 [cs.LG]
 [35] Yanzhang Lyu, Hongzhi Yin, Jun Liu, Mengyue Liu, Huan Liu, and Shizhuo Deng. 2021. Reliable Recommendation with Review-level Explanations. In
- 2021 IEEE 37th International Conference on Data Engineering (ICDE). IEEE, Chania, Greece, 1548–1558. https://doi.org/10.1109/ICDE51399.2021.00137
 [36] Gabriel Resende Machado, Eugênio Silva, and Ronaldo Ribeiro Goldschmidt. 2023. Adversarial Machine Learning in Image Classification: A Survey Toward the Defender's Perspective. Comput. Surveys 55, 1 (Jan. 2023), 1–38. https://doi.org/10.1145/3485133
- [37] Felipe Moraes, Jie Yang, Rongting Zhang, and Vanessa Murdock. 2020. The Role of Attributes in Product Quality Comparisons. In Proceedings of the 2020 Conference on Human Information Interaction and Retrieval (Vancouver BC, Canada) (CHIIR '20). Association for Computing Machinery, New York, NY, USA, 253–262. https://doi.org/10.1145/3343413.3377956
- [38] Ian E. Nielsen, Dimah Dera, Ghulam Rasool, Nidhal Bouaynaya, and Ravi P. Ramachandran. 2022. Robust Explainability: A Tutorial on Gradient-Based Attribution Methods for Deep Neural Networks. *IEEE Signal Processing Magazine* 39, 4 (July 2022), 73–84. https://doi.org/10.1109/MSP.2022.3142719 arXiv:2107.11400 [cs].
- [39] Vipin Pillai and Hamed Pirsiavash. 2021. Explainable Models with Consistent Interpretations. Proceedings of the AAAI Conference on Artificial Intelligence 35, 3 (May 2021), 2431–2439. https://doi.org/10.1609/aaai.v35i3.16344
- [40] Andrew Ross and Finale Doshi-Velez. 2018. Improving the Adversarial Robustness and Interpretability of Deep Neural Networks by Regularizing Their Input Gradients. Proceedings of the AAAI Conference on Artificial Intelligence 32, 1 (April 2018). https://doi.org/10.1609/aaai.v32i1.11504
- [41] Sungyong Seo, Jing Huang, Hao Yang, and Yan Liu. 2017. Interpretable Convolutional Neural Networks with Dual Local and Global Attention for Review Rating Prediction. In Proceedings of the Eleventh ACM Conference on Recommender Systems. ACM, Como Italy, 297–305. https: //doi.org/10.1145/3109859.3109890
- [42] Xiao Sha, Zhu Sun, and Jie Zhang. 2021. Hierarchical Attentive Knowledge Graph Embedding for Personalized Recommendation. *Electronic Commerce Research and Applications* 48 (July 2021), 101071. https://doi.org/10.1016/j.elerap.2021.101071 arXiv:1910.08288 [cs].
- [43] Carl-Johann Simon-Gabriel, Yann Ollivier, Leon Bottou, Bernhard Schölkopf, and David Lopez-Paz. 2019. First-Order Adversarial Vulnerability of Neural Networks and Input Dimension. In Proceedings of the 36th International Conference on Machine Learning (Proceedings of Machine Learning Research, Vol. 97), Kamalika Chaudhuri and Ruslan Salakhutdinov (Eds.). PMLR, 5809–5817. https://proceedings.mlr.press/v97/simon-gabriel19a.html
- [44] Dylan Slack, Sophie Hilgard, Emily Jia, Sameer Singh, and Himabindu Lakkaraju. 2020. Fooling LIME and SHAP: Adversarial Attacks on Post hoc Explanation Methods. http://arxiv.org/abs/1911.02508 arXiv:1911.02508 [cs, stat].
- [45] Akshayvarun Subramanya, Vipin Pillai, and Hamed Pirsiavash. 2019. Fooling Network Interpretation in Image Classification. http://arxiv.org/abs/ 1812.02843 arXiv:1812.02843 [cs].
- [46] Chang-You Tai, Liang-Ying Huang, Chien-Kun Huang, and Lun-Wei Ku. 2021. User-centric path reasoning towards explainable recommendation. In Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval. 879–889.
- [47] Juntao Tan, Shuyuan Xu, Yingqiang Ge, Yunqi Li, Xu Chen, and Yongfeng Zhang. 2021. Counterfactual Explainable Recommendation. In Proceedings of the 30th ACM International Conference on Information & Knowledge Management. ACM, Virtual Event Queensland Australia, 1784–1793. https: //doi.org/10.1145/3459637.3482420
- [48] Sairamvinay Vijayaraghavan and Prasant Mohapatra. 2023. Stability of Explainable Recommendation. In Proceedings of the 17th ACM Conference on Recommender Systems (Singapore, Singapore) (RecSys '23). Association for Computing Machinery, New York, NY, USA, 947–954. https: //doi.org/10.1145/3604915.3608853
- [49] Alexandra Vultureanu-Albişi and Costin Bădică. 2022. A survey on effects of adding explanations to recommender systems. Concurrency and Computation: Practice and Experience 34, 20 (Sept. 2022). https://doi.org/10.1002/cpe.6834

Sairamvinay Vijayaraghavan and Prasant Mohapatra

- [50] Nan Wang, Hongning Wang, Yiling Jia, and Yue Yin. 2018. Explainable Recommendation via Multi-Task Learning in Opinionated Text Data. In The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval. 165–174. https://doi.org/10.1145/3209978.3210010 arXiv:1806.03568 [cs].
- [51] Ning Yang, Yuchi Ma, Li Chen, and Philip S Yu. 2020. A meta-feature based unified framework for both cold-start and warm-start explainable recommendations. World Wide Web 23 (2020), 241–265.
- [52] Feng Yuan, Lina Yao, and Boualem Benatallah. 2019. Adversarial Collaborative Auto-encoder for Top-N Recommendation. In 2019 International Joint Conference on Neural Networks (IJCNN). 1–8. https://doi.org/10.1109/IJCNN.2019.8851902
- [53] Feng Yuan, Lina Yao, and Boualem Benatallah. 2019. Adversarial Collaborative Neural Network for Robust Recommendation. In Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval (Paris, France) (SIGIR'19). Association for Computing Machinery, New York, NY, USA, 1065–1068. https://doi.org/10.1145/3331184.3331321
- [54] Yongfeng Zhang and Xu Chen. 2020. Explainable Recommendation: A Survey and New Perspectives. Foundations and Trends[®] in Information Retrieval 14, 1 (2020), 1–101. https://doi.org/10.1561/1500000066
- [55] Yongfeng Zhang, Guokun Lai, Min Zhang, Yi Zhang, Yiqun Liu, and Shaoping Ma. 2014. Explicit factor models for explainable recommendation based on phrase-level sentiment analysis. In Proceedings of the 37th international ACM SIGIR conference on Research & development in information retrieval. ACM, Gold Coast Queensland Australia, 83–92. https://doi.org/10.1145/2600428.2609579
- [56] Yongfeng Zhang, Haochen Zhang, Min Zhang, Yiqun Liu, and Shaoping Ma. 2014. Do users rate or review?: boost phrase-level sentiment labeling with review-level sentiment classification. In Proceedings of the 37th international ACM SIGIR conference on Research & development in information retrieval. ACM, Gold Coast Queensland Australia, 1027–1030. https://doi.org/10.1145/2600428.2609501
- [57] Yao Zhou, Haonan Wang, Jingrui He, and Haixun Wang. 2021. From Intrinsic to Counterfactual: On the Explainability of Contextualized Recommender Systems. http://arxiv.org/abs/2110.14844 arXiv:2110.14844 [cs].