석 사 학 위 논 문
Master's Thesis

상품 평가 품질 조작에 견고한 추천 시스템

A Robust Recommendation System
Against Review Quality Manipulation

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심 동 진 (沈 東 鎭 Sim, Dongjin)

한 국 과 학 기 술 원

Korea Advanced Institute of Science and Technology

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A Robust Recommendation System Against Review Quality Manipulation

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The study was conducted in accordance with Code of Research Ethics[1].

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초 록

추천 시스템은 사용자들의 구매 결정에 주요한 영향을 주기 때문에 악의적인 조작의 표적이 되어왔다. 대표적인 추천 방법은 상품에 대한 평가들이 정직하다는 가정하에 사용자의 기호정보를 분석하는 협업 필터링 방법이다. 하지만 협업 필터링 방법은 거짓된 상품 평가를 주입하는 실링 공격에 의해 조작될 위험이 있다. 이로 인해 실링 공격의 영향력을 낮추려는 여러 방법이 제안되었다. 최근에는, 많은 추천 시스템은 사용자에게 상품 평가의 품질을 평가할 수 있게 한다. 거짓된 상품 평가는 사용자들에 의해 낮은 품질로 분류될 것이라는 가정하에 연구자들은 상품 평가의 품질을 고려한 추천을 통해 실링 공격을 극복하고자 하였다. 하지만 이러한 추천 방법은 거짓된 품질 평가 데이터가 주입된다면 오히려 조작의 정도가 심해질 위험이 있다. 본 논문에선 상품 평가의 품질을 조작하려는 시도가 있더라도 상품 평가의 진실한 품질을 추정하는 견고한 추천 방법을 제안한다. 실제 데이터를 토대로 한 실험 결과를 통해 제안한 방법이 상품 평가의 거짓된 품질 평가를 고려하지 않는 방법보다 최대 20배 견고함을 보였다.

핵 심 낱 말 견고한 추천 시스템, 협업 필터링, 추천 시스템 조작, 상품 평가 품질 측정

Abstract

Recommendation systems influence decision making and have become attractive targets of manipulation. Collaborative filtering, widely adopted in recommendation systems, exploits the observed reviews given by users to provide personalized recommendations under the assumption that all users honestly rate items. Unfortunately, shilling attacks which inject fake reviews can easily manipulate the systems with the naive assumption. Several approaches have been proposed to mitigate the effect of shilling attack. Recently, some researchers have been interested in the fact that most recommendation systems encourage users to write reviews, as well as rate the helpfulness of reviews written by other users. With the assumption that users will evaluate the helpfulness of fake reviews as low, they proposed recommendation systems considering the helpfulness as the quality of reviews.

However, those systems are vulnerable to attacks that inject fake helpfulness ratings to improve the quality of fake reviews. We propose a robust recommendation system to overcome such review quality manipulation attacks. The proposed approach estimates the true quality of reviews even in the presence of both injected fake reviews and helpfulness ratings. Experimental results on a real-world dataset demonstrate the robustness of our method. The proposed approach yields up to 20 times more robust recommendation results than the approaches that do not consider review quality manipulation.

Keywords Robust recommendation system, Collaborative filtering, Shilling attack, Review quality

Contents

List of Tables

List of Figures

Chapter 1. Introduction

Since recommendation systems influence purchase decisions, their positive recommendation can lead to significant monetary benefit for product sellers. According to [1], increasing the overall rating of a business by one star on Yelp[1] can increase the revenue of the business by 9%. Unfortunately, the strong impact of recommendation systems has attracted malicious attackers who try to bias recommendation results to manipulate the overall rating of their target items.

Matrix factorization(MF) model based collaborative filtering(CF) [6] is one of the most common approaches for the recommendation. MF infers users' tastes and items' attributes based on the observed ratings of users for items and recommends products whose attributes match a user's taste. MF naively assumes that all the observed ratings are conducted by honest users. In practice, however, this assumption is easily violated because of the presence of attackers. Due to the open nature of recommendation systems, attackers can inject fake reviews and ratings to increase the overall rating of their target items on the recommendation system. Such injections with intent to bias recommendation results are called shilling attacks. There are a number of studies about shilling attack strategies [2, 3, 4, 5] and robust recommendation methods to prevent shilling attacks [8, 9, 10, 11, 12, 14].

Recent studies [16, 17] focused on the following dual roles of users in real-world recommendation systems. Users play a role of the reviewer of items by writing reviews about items in the form of a numeric rating score and review text. In addition, they play a role of the helpfulness rater of reviews. Namely, they rate the helpfulness score for reviews written by other users. Figure 1.1a contains a review of *Captain America: Civil War (DVD)* written by user *lmmyvasi29* with a 5-star rating. Figure 1.1b shows that other users rate the helpfulness of the review in Figure 1.1a.

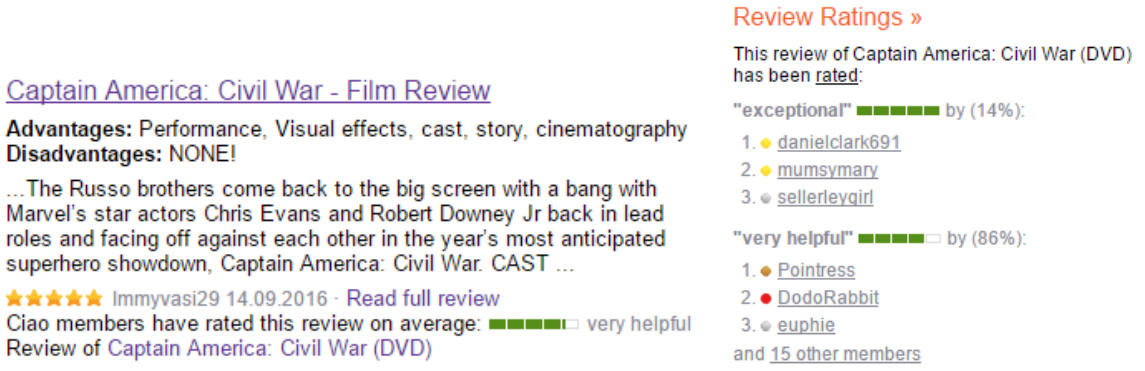
Wang et al. [17] considered helpfulness rating as users' implicit feedback about items and incorporated the helpfulness rater role in recommendation systems to mitigate data sparsity and cold-start problems. Raghavan et al. [16] proposed collaborative filtering

[1] www.yelp.com

that considers the quality of review to improve performance in the presence of fake reviews. Assuming that fake reviews receive a negative helpfulness rating, the proposed model measures the quality of a review by aggregating the helpfulness ratings for the review and lowers the impact of poor quality reviews on optimizing parameters of recommendation model. They show that incorporating review helpfulness rating information has potential benefits of improving the performance and robustness of recommendation systems.

However, they did not deal with fake review helpfulness ratings. After injecting fake reviews, malicious attackers can easily inject fake helpfulness ratings to promote the quality of fake reviews. They did not consider review quality manipulations that can promote the negative effect of fake reviews.

We propose a robust recommendation model even in the presence of both fake reviews and helpfulness ratings via a new review quality measure which estimates the true quality of reviews. Our approach consists of three stages. The first stage involves mapping users to a feature vector space to find groups of users suspected of being shillers. In the second stage, the quality of each review is measured based on the Bayesian weighted mean of the helpfulness ratings associated with each review. If a helpfulness rater is suspicious, that is, very similar to a review writer, his/her helpfulness rating for the review should have a low weight. In the final stage, the quality of each review measured in the previous stages is used as input for collaborative filtering. We adopt the cost function suggested by [7, 16]. Simulating various attacks on a real-world dataset, we demonstrate the effectiveness of the proposed method. Experimental results show that our method mitigates the effect



(a) An item review example (b) A helpfulness rating example

Figure 1.1: Item review and helpfulness rating example from Ciao

of manipulating review quality compared with other methods. In specific, our method yields up to 20 times more robust recommendation results than the approaches that do not consider attacks.

The thesis is organized as follows. Chapter 2 presents the background. Related work is described in Chapter 3. Our problem is defined in Chapter 4 and Chapter 5 describe our approach. In Chapter 6 presents the experimental methodology used to evaluate the robustness of our approach and results of our experiment. Finally, we conclude in Chapter 7.

Chapter 2. Background

2.1 Notation

Throughout the thesis, sets are denoted as italic capital letters and matrices/tensors are written as boldface capital letters. Let $U = \{u_1, u_2, \ldots, u_n\}$ and $I = \{i_1, i_2, \ldots, i_m\}$ be a set of users and items where n and m are the number of users and items, respectively. In recommendation systems, users can rate items in the form of a numeric rating score accompanied by review text. We use the term *'item rating'* and *'review'* to represent a numeric rating score for an item. We use the matrix $\boldsymbol{R} \in \mathbb{R}^{n \times m}$ to denote the item rating matrix where an entry $R_{u,i}$ indicates the item rating score of user u for item i. Note that the item rating matrix $\boldsymbol{R}$ is sparse since users usually rate a small set of items. If user u did not rate item i, then we assign "?" to the missing item rating $\boldsymbol{R}_{u,i}$. $IR = \{(u, i, ir) | u \in U, i \in I, ir = \boldsymbol{R}_{u,i}, ir \neq ?\}$ to represents item rating dataset where (u, i, ir) means user u rates item i with score ir.

Many recommendation systems allow users to evaluate the helpfulness of other users' reviews in order to improve the user experience. After reading review content (numeric rating score and review text), users give the review helpfulness score in the form of a numeric rating score. We use the term *'helpfulness rating'* to indicate such a numeric rating score for a review. (u_a, u_b, i_c, hr) means that user u_a gives helpfulness score hr to the review of user u_b for item i_c. We use $\boldsymbol{H} \in \mathbb{R}^{n \times n \times m}$ to denote the helpfulness rating tensor where an entry $\boldsymbol{H}_{a,b,c}$ indicates the review helpfulness score that user a gives to the review of user b for item c. Similarly with item rating dataset, $HR = \{(u_a, u_b, i, hr) | u_a, u_b \in U, i \in I, hr = \boldsymbol{H}_{a,b,c}, hr \neq ?\}$ represents helpfulness rating dataset.

Since we consider an attacker who injects shillers, we use U^g and U^f to denote the set of genuine users and shillers, respectively. Genuine item rating and helpfulness rating dataset are denoted by $IR^g = \{(u, i, ir) | u \in U^g\}$ and $HR^g = \{(u, v, i, hr) | u \in U^g\}$, respectively. Similarly, fake item rating and helpfulness rating dataset are denoted by $IR^f = \{(u, i, ir) | u \in U^f\}$ and $HR^f = \{(u, v, i, hr) | u \in U^f\}$, respectively. Unless otherwise noted, the range of item rating score is from 1 to 5, and helpfulness rating

score ranges from 0 to 5.

2.2 Matrix Factorization Based Collaborative Filtering

The objective of collaborative filtering (CF) is to predict the value of the missing entries in an item rating matrix. Matrix factorization (MF) is the popular technique to predict the missing entries in a matrix by inferring latent patterns from the observed entries of the matrix. In the context of CF, MF infers latent features of user and items based on the known item ratings of users for items. It decomposes a item rating matrix $\boldsymbol{R}$ into two latent matrices $\boldsymbol{U} \in \mathbb{R}^{n \times d}$ and $\boldsymbol{V} \in \mathbb{R}^{d \times m}$ corresponding latent features of user and item, respectively, where the d is the number of latent features. In specific, MF optimizes the two matrices $\boldsymbol{U}$ and $\boldsymbol{V}$ by minimizing the following cost function which is the sum of prediction error terms and regularization terms.

$$Cost(\boldsymbol{U}, \boldsymbol{V} | \boldsymbol{R}) = \sum_{\boldsymbol{R}_{i,j} \neq ?} (\boldsymbol{R}_{i,j} - (\boldsymbol{UV})_{i,j})^2 + \lambda(||\boldsymbol{U}||_F^2 + ||\boldsymbol{V}||_F^2) \tag{2.1}$$

After obtaining the optimized $\boldsymbol{U}$ and $\boldsymbol{V}$, all missing entries in the item rating matrix $\boldsymbol{R}$ are predicted via the dense matrix $\boldsymbol{UV}$ which is the product of $\boldsymbol{U}$ and $\boldsymbol{V}$. We construct a very simple example (Figure 2.1) as follows. The item set of the item rating matrix comprises two romance movies, two horror movies, and one bad movie. The user set consists of two romance lovers and two horror lovers. After performing MF on the item rating matrix $\boldsymbol{R}$, prediction matrix $\boldsymbol{UV}$ captures the tastes of users and judges that users would not like the bad movie.

		Romance		*Horror*		*Bad*
		Movie 1	Movie 2	Movie 3	Movie 4	Movie 5
Romance Lovers	User 1	5	5	?	2	?
	User 2	4	?	2	?	1
Horror Lovers	User 3	2	?	4	4	1
	User 4	?	2	5	5	?

(a) Rating matrix $\boldsymbol{R}$

		Romance		*Horror*		*Bad*
		Movie 1	Movie 2	Movie 3	Movie 4	Movie 5
Romance Lovers	User 1	5	5	2.1	2	1.2
	User 2	4	3.8	2	2	1
Horror Lovers	User 3	2	1	4	4	1
	User 4	3.7	2	5	5	1.4

(b) Prediction matrix $\boldsymbol{UV}$

Figure 2.1: Matrix factorization example

2.3 Shilling Attack

There are malicious attackers who try to manipulate a CF-based recommendation system to gain benefit. These attackers attempt to manipulate the recommendation system by injecting fraudulent user (Shillers) and fake rating data. The attempts are called 'Shilling attacks.' Shilling attacks are divided into two categories: *push attack* and *nuke attack*. The push attack generates shillers with high ratings on an item to promote its recommendation score. On the other hand, the nuke attack injects shillers with low ratings on an item to decrease its popularity. However, fake item rating injection only for target items is not enough to manipulate a CF-based recommendation system, because CF predicts missing item ratings of genuine users in the way attackers wish if tastes of genuine users are similar to those of shillers. Therefore, shillers have to mimic rating behaviors of genuine users to fully exploit the principle of collaborative filtering. There are various attack models on how to mimic rating behavior of genuine users: Random attack, Average attack, Bandwagon attack [2, 3, 4, 5]. In the context of push attack, Random attack injects shillers who give the highest rating to their target items and rate the randomly chosen items around the overall mean. Average attack generates shillers that give the highest rating to their target items and the mean rating of each item to randomly chosen items. Bandwagon attack consists of shillers whose ratings for their target items and popular items are maximum.

The figure 2.2 shows an example of shilling attack and its effect. We inject two shillers whose aims are boosting the prediction score of the bad movie. Shillers rate the bad movie with the highest possible rating value, i.e. 5, and rate other movies in a similar

		Romance		*Horror*		*Bad*
		Movie 1	Movie 2	Movie 3	Movie 4	Movie 5
Romance Lovers	User 1	5	5	?	2	?
	User 2	4	?	2	?	1
Horror Lovers	User 3	2	?	4	4	1
	User 4	?	2	5	5	?
Shillers	User 5	?	3	?	3	5
	User 6	3	?	3	?	5

(a) Rating matrix $\boldsymbol{R}$

		Romance		*Horror*		*Bad*
		Movie 1	Movie 2	Movie 3	Movie 4	Movie 5
Romance Lovers	User 1	5	5	5	2	5
	User 2	3	1	3	4	1
Horror Lovers	User 3	3	1	3	4	1
	User 4	5	2	5	5	3.9
Shillers	User 5	4.3	3	4.3	3	5
	User 6	3	3.2	3	1	5

(b) Prediction matrix $\boldsymbol{UV}$

Figure 2.2: Matrix factorization in the presence of shilling attack

way to other genuine users. Matrix factoring misjudges the prediction scores of the bad movie because it has to reduce the error of the fake ratings to optimize its cost function. Compared with figure 2.1, figure 2.2 contains high predicted rating of genuine users for the bad movie.

2.4 Weighted Matrix Factorization for Robust Collaborative Filtering

The reason MF is vulnerable to shilling attack is that MF does not consider the presence of fake item ratings. Therefore, various attempts have been proposed to eliminate or mitigate the impact of fake item ratings on MF. The cost functions used in these attempts are expressed in the form of weighted matrix factorization(WMF) [7].

$$Cost(\boldsymbol{U}, \boldsymbol{V} | \boldsymbol{W}, \boldsymbol{R}) = \sum_{\boldsymbol{R}_{u,i} \neq ?} \boldsymbol{W}_{u,i} (\boldsymbol{R}_{u,i} - (\boldsymbol{U}\boldsymbol{V})_{u,i})^2 + \lambda(||\boldsymbol{U}||_F^2 + ||\boldsymbol{V}||_F^2) \tag{2.2}$$

$\boldsymbol{W} \in \mathbb{R}^{n \times m}$ is a weight matrix where $\boldsymbol{W}_{u,i}$ is the weight for the item rating $\boldsymbol{R}_{u,i}$. In this cost function, prediction error term changes from sum of squared errors to weighted sum of squared errors, which allows item ratings whose weight is small to have significant prediction error. This property helps WMF based on weight matrix where fake item ratings have a small weight to yield desirable predictions robust to fake item ratings.

Figure 2.3 shows an example of WMF where the weights of genuine reviews are larger than those of fake reviews. With well-assigned weight matrix, latent features of users and items are optimized to describe genuine review better, so shillers fail to manipulate prediction of genuine users for the bad movie.

However, if the weights of fake item ratings are large, then WMF would yield more

		Romance		Horror		Bad
		Movie 1	Movie 2	Movie 3	Movie 4	Movie 5
Romance Lovers	User 1	5	5	?	2	?
	User 2	4	?	2	?	1
Horror Lovers	User 3	2	?	4	4	1
	User 4	?	2	5	5	?
Shillers	User 5	?	3	?	3	5
	User 6	3	?	3	?	5

(a) Rating matrix $\boldsymbol{R}$

		Romance		Horror		Bad
		Movie 1	Movie 2	Movie 3	Movie 4	Movie 5
Romance Lovers	User 1	0.9	0.9		0.9	
	User 2	0.9		0.9		0.9
Horror Lovers	User 3	0.9		0.9	0.9	0.9
	User 4		0.9	0.9	0.9	
Shillers	User 5		0.1		0.1	0.1
	User 6	0.1		0.1		0.1

(b) Weight matrix $\boldsymbol{W}$

		Romance		Horror		Bad
		Movie 1	Movie 2	Movie 3	Movie 4	Movie 5
Romance Lovers	User 1	5	5	2.2	2	1.3
	User 2	4	3.8	2	1.9	1.1
Horror Lovers	User 3	2	1	4	4	1
	User 4	3.8	2	5	5	1.5
Shillers	User 5	4.6	3.5	4	3.9	1.5
	User 6	3.7	2.5	3.6	3.6	1.3

(c) Prediction matrix $\boldsymbol{U}\boldsymbol{V}$

Figure 2.3: Weighted matrix factorization with a well assigned weight matrix

manipulated predictions. Therefore, the key to WMF for robust CF is how to build a good weight matrix $\boldsymbol{W}$, in other words, how to capture fake item ratings and decrease their weights.

Chapter 3. Related Work

This section describes various studies to build a weight matrix. The common goal is to detect suspicious item ratings and assign low weight.

Early research for robust CF focused on detecting manipulated ratings by only examining a given rating matrix. For example, Mehta et al. [8] proposed Robust Matrix Factorization (RMF) using M-estimators to bound the effect of outliers and noisy data. [10, 11, 9] apply PCA-based variable selection to detect suspicious users in unsupervised setting.

Recently, many researchers have started to incorporate various types of additional information into the recommendation algorithm in order to improve the accuracy of the recommendation algorithm. In response to this trend, defense mechanisms with additional information have also been proposed. Two popular additional information used in the recommendation algorithm are review text and review helpfulness rating information.

Text-based approaches [12, 14, 13, 15] exploit review textual features and meta features to detect fake reviews. [12] detects spam reviews by finding (near) duplicate reviews and using learned logistic regression with manually labeled data. Ott et al. [14] collected training data through crowd-sourcing and accurately classified the deceptiveness of reviews based on n-grams. However, text-based approaches have several drawbacks. They require labeled data to train an accurate classifier, and the labeled data depends on the item domain.

Many review sites adopt votes on the helpfulness of reviews. With helpfulness ratings, users can examine the helpfulness of reviews with statistics such as "90 (out of 100) people found this review helpful" or "40 members have rated this review on average (somewhat helpful)". Some research [15, 16] exploit helpfulness rating information to measure the quality of reviews. Kim et al. [15] proposed the measure to quantify the quality of a review by aggregating helpfulness ratings for the review.

$$Quality(review(u,i)) = \frac{1}{N} \sum_{\boldsymbol{H}_{v,u,i} \neq ?} \boldsymbol{H}_{v,u,i} \tag{3.1}$$

where N is the number of helpfulness ratings for review (item rating) $\boldsymbol{R}_{u,i}$. Under the

assumption that spam reviews would receive low helpfulness ratings, [16] builds the weight matrix used in the WMF with the above review quality measure. They showed that review helpfulness could improve the overall performance of recommendation in the presence of spam review.

Chapter 4. Motivation

4.1 Review Quality Manipulation

The review quality measure represented by the equation 3.1 relies on the naive assumption that all helpfulness ratings are genuine. However, this assumption is easily violated if attackers inject fake helpfulness ratings to promote the quality of their fake reviews. From an adversarial perspective, the cost of fake helpfulness rating injection would be not much more expensive than the cost of fake item rating injection. Therefore, when constructing weight matrix based on review helpfulness ratings, attempts to review quality manipulation should be thoroughly taken into account.

Figure 4.1 shows the case an attacker succeeds in manipulating the quality of fake reviews. The fake item ratings for the bad movie have a larger weight than other genuine item ratings as shown in Figure 4.1. Due to the manipulated weight matrix, the recommendation results are heavily affected by fake reviews.

		Romance		Horror		Bad
		Movie 1	Movie 2	Movie 3	Movie 4	Movie 5
Romance Lovers	User 1	5	5	?	2	?
	User 2	4	?	2	?	1
Horror Lovers	User 3	2	?	4	4	1
	User 4	?	2	5	5	?
Shillers	User 5	?	3	?	3	5
	User 6	3	?	3	?	5

(a) Rating matrix $\boldsymbol{R}$

		Romance		Horror		Bad
		Movie 1	Movie 2	Movie 3	Movie 4	Movie 5
Romance Lovers	User 1	0.1	0.1		0.1	
	User 2	0.1		0.1		0.1
Horror Lovers	User 3	0.1		0.1	0.1	0.1
	User 4		0.1	0.1	0.1	
Shillers	User 5		0.9		0.9	0.9
	User 6	0.9		0.9		0.9

(b) Weight matrix $\boldsymbol{W}$

		Romance		Horror		Bad
		Movie 1	Movie 2	Movie 3	Movie 4	Movie 5
Romance Lovers	User 1	4.5	5	2.4	2.2	5
	User 2	1.7	1.9	1.3	1.2	2.8
Horror Lovers	User 3	1	1	3.8	4	1.8
	User 4	2.9	2.1	4.9	5	5
Shillers	User 5	3	3	3	3	5
	User 6	3	3	3	3	5

(c) Prediction matrix $\boldsymbol{UV}$

Figure 4.1: Weighted matrix factorization with a badly assigned weight matrix

4.2 Attack Model

In this section, we define an attack model. The attack model injects both fake item rating (review) and fake helpfulness rating in order to simulate a push attack. We only focus on push attack, because push attack is a more direct way to promote monetary benefit than nuke attack. We leave nuke attack for future work. Our attack model involves in injecting fake item rating and helpfulness rating dataset, IR^f and HR^f.

4.2.1 Fake Item Rating Injection

Our attack model injects fake item ratings to manipulate the predicted rating scores of collaborative filtering for the target items. Popular strategies for fake item rating injection are Random attack, Average attack, and Bandwagon attack. Since Random attack is known to be ineffective, we focus on Average attack and Bandwagon attack. Similar to [5], from the view of each shiller, the item set I is partitioned into 4 subsets, $I^{target}, I^{popular}, I^{filler}$ and I^{none} where I^{target} is a set of target items; $I^{popular}$ is a set of popular items that many genuine users like; I^{filler} is a set of randomly chosen items, called filler items; I^{none} is the set of the remaining items, i.e. $I^{none} = I - I^{target} - I^{popular} - I^{filler}$. For each shillers, item ratings for I_{target}, $I_{popular}$ and I_{filler} are assigned as follows: First, we assign the highest possible value to the item rating scores of shillers for I_{target} Secondly, to make the rating behavior of shillers similar to that of genuine users, the item rating scores for I_{filler} are distributed around the average item rating for filler items. Finally, we let shillers give the highest item rating scores for $I_{popular}$ to increase similarity between shillers and a large number of genuine users. Note that the size of each subset can vary. We assume a recommendation system manager could easily detect attacks associated with the too big size of I_{target}, I_{filler}, $I_{popular}$. Therefore, we limit the size of each subset to less than 1% of the size of an entire item set I. In summary, the general form of fake item rating dataset IR^f is defined as follows.

$$IR^f = \bigcup_{u^f \in U^f} \{(u^f, i, ir_{max}) | i \in I^{target}\} \cup \{(u^f, i, ir_{avg}(i)) | i \in I^{filler}\} \cup \{(u^f, i, ir_{max}) | i \in I^{popular}\} \tag{4.1}$$

ir_{max} is the highest value on the item rating scale and $ir_{avg}(i)$ is the average item rating for item i.

4.2.2 Fake Helpfulness Rating Injection

In addition to fake item rating injection, our attack model injects fake helpfulness ratings to manipulate review quality. The injection makes our study different from existing attack models. We set shiller's helpfulness ratings for fake reviews to the highest value. Additionally, we inject random helpfulness rating of shillers for randomly chosen reviews aimed at avoiding attack detections Formally, fake helpfulness rating dataset

HR^f is defined as follows:

$$HR^f = \bigcup_{u^f \in U^f} \{(u^f, v, i, hr_{max}) | v \in U^f, i \in I^{target}\} \cup \{(u^f, v, i, hr_{random}) | v \in U^g, i \in I, \boldsymbol{R}_{v,i} \neq ?\} \tag{4.2}$$

hr_{max} is the highest value on the helpfulness rating scale and hr_{random} represents random rating.

In the presence of fake helpfulness ratings, computing the quality of a review as the average of helpfulness ratings misjudges fake reviews as high quality, which increases the negative impact of fake reviews on collaborative filtering considering review quality.

4.3 Problem Definition

With the proposed attack model, we define our problem as follows: **given** reviews and helpfulness ratings in the presence of fake data injected by the attack model, **estimate** the true quality of reviews to construct the weight matrix of WMF. We express our problem as follows.

$$Quality(review(u, i)) = F(Helpfulness\ ratings\ of\ review(u, i)\ under\ attack) \tag{4.3}$$

Then the problem can be divided into two sub-problems. One is to detect fake helpfulness ratings, and the other is to devise a robust estimator function F that produces consistent review quality regardless of the presence of fake helpfulness ratings.

Chapter 5. Proposed Method

This section describes our method in detail. The following sections describe how to capture suspicious helpfulness ratings and how to estimate the true quality of reviews.

5.1 User2Vec

Recently, various prediction tasks [18, 19, 20, 21] have improved performance by learning the desirable features themselves, instead of manually determining domain-specific features. Skip-gram model [18] is a popular model proposed for natural language processing task by Mikolov et al. The goal of the Skip-gram model is to capture semantic relationships between words. With the hypothesis that words which frequently appear together in sentences have semantic relationships, the Skip-gram model takes large real-world text corpus as training data and learns feature representations for words. In specific, it maps words to a feature space such that words frequently appear together in sentences have similar feature vectors. The Skip-gram model is widely adopted due to the efficiency and ability to capture useful relationships in the text data. Inspired by the success of the Skip-gram model, some researchers apply the Skip-gram model to learning a mapping of vertices of a network to vectors which encode social relation [20, 21]. With the assumption random walk traces contain social relation between vertices, they generate samples of random walk traces as sequences of vertices, feed them into the Skip-gram model.

In this thesis, we propose User2Vec, an algorithm for learning feature representations for users in recommendation system to detect suspicious relationships between users. [18] uses real-world sentences as sequences of semantically related words. [20, 21] generates random walk traces as sequences of socially related vertices to obtain useful features for various prediction tasks. Similar to such approaches, we generate user pairs which might contribute shilling attacks and feed them into the Skip-gram model to obtain feature representations of users which are useful to detect shillers.

To generate sequences of attack-related users, we focus on behaviors of shillers. Several studies [10, 11] reported that shillers need to work together to maximize the effect

of their attack. This strategy is referred to as group attack. In our attack model, shillers equally give the highest item rating to target items and the highest helpfulness rating to their fake reviews. Taking this into consideration, we regard following relationships between users as clues to the group attack.

1. Both user X and Y give ir_{max} for an item
2. Both user X and Y give hr_{max} for a review
3. User X gives hr_{max} for a review written by user Y

We refer to the users rate an item with ir_{max} as *enthusiasts* for the item. Similarly, we refer to the users rate the helpfulness of a review with hr_{max} as *supporters* for the review. The first (second) relationship represents the pair of enthusiasts (supporters) whose opinions about some item (review) are same. If user u_c and u_d always rate in the same way items or reviews, then it is reasonable to suspect that u_c and u_d are performing group attack. The last relationship indicates the pair of a reviewer and a supporter. If user u_a always gives the maximum helpfulness rating to all reviews written by another user u_b, then one can doubt that user u_a intentionally promotes the influence of user u_b. Note that we only target the ratings with the highest score only since we focus on push attacks. Of course, pairs of genuine users could reveal clues to the group attack due to the coincidence of opinions about items or reviews. However, all shillers have to involve in many connections through the relationships associated with group attack as a necessity to maximize the degree of manipulation. With this in mind, we suspect the truthfulness of a helpfulness rating if the rater and the reviewer are frequently connected through the mentioned relationships.

User2Vec consists of two steps. In the first step, we sample user pairs that reveal clues to the group attack. Sampling user pairs corresponding to the first relationship proceeds as follows. Among the items having at least two enthusiasts, we first sample an item with the probability proportional to the cardinality of the users associated with the item and choose two reviewers for the sampled item uniformly at random. Sampling user pairs corresponding to both the second and last relationship involves in sampling reviews. The probability of sampling a review is proportional to the number of the helpfulness raters for the review. With a sampled review, we choose two supporters to get the

sample related to the second relationship. To generate sample corresponding to the last relationship, we sample one supporter and produce a pair of reviewer and supporter. In the last step, we feed the sampled user pairs into the Skip-gram model and obtain feature vectors of users. We expect the obtained feature vectors encode group attack patterns. In other words, shillers are very closely located to each other in the feature space, while genuine users are scattered. Note that User2Vec which places the shillers very close to each other in the feature space does not guarantee that genuine users are positioned away from each other in the feature space. However, if the dimension of the feature space is moderately high, the probability that the location of two arbitrarily selected users is close is very small. Therefore, although there is a risk of judging false positives, we judge that the relationship between two users with very high similarity is not trustful and define the suspiciousness of a helpfulness rating as a function of the similarity between the feature vectors of the helpfulness rater and the reviewer.

5.2 Bayesian Weighted Mean

In this section, we explain Bayesian Weighted Mean to estimate the true quality of reviews. We assume that the true quality of a review can be estimated by the mean of genuine helpfulness ratings. However, in the presence of fake helpfulness ratings, we need to estimate the true quality of a review by the weighted mean of helpfulness ratings where the fake helpfulness ratings have very low weight. If the number of helpfulness ratings is sufficiently high, then this estimation get high confidence. However, for reviews with have few helpfulness ratings or only fake helpfulness ratings, the weighted mean is not a robust estimator for such reviews. Say a fake review which has only fake helpfulness ratings. Then the output of weighted mean is biased toward fake helpfulness ratings even if the weight of fake helpfulness ratings is almost zero. With all of these things in mind, we define the following review quality measure to estimate the true quality of a review.

$$Quality(u,i) = \frac{w_{prior} Q_{default} + \sum_{v \in \{x | \boldsymbol{H}_{v,u,i} \neq ?\}} T(v,u) \times \boldsymbol{H}_{v,u,i}}{w_{prior} + \sum_{v \in \{x | \boldsymbol{H}_{v,u,i} \neq ?\}} T(v,u)} \tag{5.1}$$

We take Bayesian approach that incorporates both a prior belief and a weighted mean of review helpfulness ratings. The prior quality $Q_{default}$ works as prior belief. w_{prior} is the weight given to the prior belief. In this work, we set $Q_{default}$ as the mean of helpfulness

rating range (e.g. 2.5 in the range from 0 to 5), and w_{prior} as 1. The weight of a helpfulness rating is determined by the following function $T : U \times U \rightarrow R$.

$$T(v,u) = \begin{cases} exp(-\mu \times (cosine(userVec_v, userVec_u) - \theta)) & \text{if } cosine(userVec_v, userVec_u) \geq \theta \\ 1 & \text{otherwise} \end{cases} \tag{5.2}$$

$userVec_u$ denotes the feature vector of user u obtained from User2Vec. The function T takes a rater and a reviewer, and output the trustfulness of the relationship between them. T penalizes the trustfulness if the cosine similarity between their feature vectors is larger than the threshold θ. As mentioned earlier, this policy might lower the weight of genuine helpfulness ratings, but the likelihood of making such a misjudgment is very low in the moderately high dimensional feature spaces. μ is a constant for amplification of similarity. In this work, we set the θ as 0.8 and the μ as 100.

With the robust estimator, the quality of reviews with few helpfulness ratings will be close to the default quality $Q_{default}$, while reviews whose helpfulness raters are not that similar to the reviewer will have a quality score close to its average helpfulness rating. Most importantly, reviews with many untrustful helpfulness ratings will have a helpfulness score close to the default quality $Q_{default}$. In other words, our measure prevents fake helpfulness ratings from manipulating the quality of their fake review.

Algorithm 1 User2Vec algorithm

function USER2VEC(dimensions d, num_samples n, item rating matrix $\boldsymbol{R}$, helpfulness rating tensor $\boldsymbol{H}$)

Initialize *clues* to *empty*

for $iter = 1$ to n **do**

append EnthusiastPair($\boldsymbol{R}$) to *clues*

append SupporterPair($\boldsymbol{H}$) to *clues*

append ReviewerSupporterPair($\boldsymbol{H}$) to *clues*

end for

$userVec$ = Skip-Gram($clues, d$)

return $userVec$

end function

function ENTHUSIASTPAIR(item rating matrix $\boldsymbol{R}$)

let $Enthusiast(item)$ be $\{u|\boldsymbol{R}_{u,item} = ir_{max}\}$

let EI be $\{item||Enthusiast(item)| \geq 2\}$

sample item i from EI with the prob. proportional to the cardinality of $Enthusiast(i)$

sample user u, v from $Enthusiast(i)$ uniformly at random

return (u, v)

end function

function SUPPORTERPAIR(helpfulness rating tensor $\boldsymbol{H}$)

let $Supporter(u, i)$ be $\{v|\boldsymbol{H}_{v,u,i} = hr_{max}\}$

let SU be $\{(u, i)||Supporter(u, i)| \geq 2\}$

sample review (u, i) from SU with the prob. proportional to the cardinality of $Supporter(u, i)$

sample user u_a, u_b from $Supporter(u, i)$ uniformly at random

return (u_a, u_b)

end function

function REVIEWERSUPPORTERPAIR(helpfulness rating tensor $\boldsymbol{H}$)

let $Supporter(u, i)$ be $\{v|\boldsymbol{H}_{v,u,i} = hr_{max}\}$

let SU be $\{(u, i)||Supporter(u, i)| \geq 1\}$

sample review (u, i) from SU with the prob. proportional to the cardinality of $Supporter(u, i)$

sample user v from $Supporter(u, i)$ uniformly at random

return (u, v)

end function

Algorithm 2 Robust recommendation system

function RRS(dimensions d, num_samples n, item rating matrix $\boldsymbol{R}$, helpfulness rating tensor $\boldsymbol{H}$)

$userVec = \text{User2Vec}(d, n, \boldsymbol{R}, \boldsymbol{H})$

for all review (u, i) **do**

$\boldsymbol{W}_{u,i} = Quality(u, i) = \frac{w_{prior} Q_{default} + \sum_{v \in \{x | \boldsymbol{H}_{v,u,i} \neq ?\}} T(v,u) \times \boldsymbol{H}_{v,u,i}}{w_{prior} + \sum_{v \in \{x | \boldsymbol{H}_{v,u,i} \neq ?\}} T(v,u)}$

end for

Optimize $Cost(\boldsymbol{U}, \boldsymbol{V} | \boldsymbol{W}, \boldsymbol{R}) = \sum_{\boldsymbol{R}_{i,j} \neq ?} \boldsymbol{W}_{i,j} (\boldsymbol{R}_{i,j} - (\boldsymbol{U}\boldsymbol{V})_{i,j})^2 + \lambda(||\boldsymbol{U}||_F^2 + ||\boldsymbol{V}||_F^2)$

return Optimized $\boldsymbol{U}$ and $\boldsymbol{V}$

end function

Chapter 6. Experiment

We conduct experiments on a real-world dataset to demonstrate the effectiveness of the proposed method. Especially, we aim to answer the following questions.

- How well does the proposed review quality measure estimate the true quality of reviews?
- Does the proposed review quality measure lead to prediction robust against review quality manipulation?
- How much is predictive accuracy sacrificed for adding robustness?

6.1 Experimental Setting

We use the publicly available dataset provided by [22], namely CiaoDVD. The CiaoDVD dataset contains review and helpfulness rating information from ciao.dvd.co.uk where users rate DVDs and others' reviews. In the CiaoDVD dataset, users can rate items with a score from 1 to 5 as a reviewer, and rate the helpfulness of reviews with a score from 0 to 5 as a helpfulness rater. From the original dataset, we filter out the reviewers who rated less than five items and items which received less than five ratings. The statistics of the resulting dataset are shown in Table 6.1.

Table 6.1: Statistics of CiaoDVD dataset

Features	**CiaoDVD**
Reviewers	1822
Items	2069
Reviews	28374
Helpfulness Rater	27900
Helpfulness Rating	661040

We assume the original data is genuine. To this data, we inject shillers, item ratings and helpfulness ratings as mentioned in Chapter 4. Attack size, i.e. the number of

shillers, ranges from 1% to 3% of total users. Filler size is the number of I^{filler} and popular size is the number of I^{filler}. We restrict the sum of filler size and popular size from exceeding 1% of the total number of items. We assume attacks with larger attack sizes and filler/popular sizes would be detected easily, so we decide to exclude them in our experiment setting. For performance evaluation, we perform 10-fold cross validation. In each fold, the test set contains random 10% original reviews, and the training set contains the remaining 90% original reviews and all the fake reviews. We choose target items of I^{target} as items which have been rated by at least 1% users with below the median of the rating scale (3 in our rating scale [1,5]). $I^{popular}$ consists of items rated items by at least 1% users with the ir_{max}. Note that I^{filler} is randomly selected for each shiller.

6.2 Comparison of Recommendation Models

We compare the proposed model with two basic recommendation models. Recommendation models used in the experiments are defined as:

- **MF**: Matrix factorization on item rating matrix without considering review quality. In other words, it does not use helpfulness rating dataset.
- **Naive WMF**: Weighted matrix factorization on item rating matrix. Its weight matrix is constructed with the naive review quality measure.
- **Robust WMF**: Weighted matrix factorization on item rating matrix. Its weight matrix is generated by the proposed review quality measure.

6.3 Metrics

Average quality of reviews measures the average quality of reviews belonging to each category. We compare the average quality values of fake reviews and genuine reviews to find out the robustness of a quality measure. A robust quality measure should produce the small average quality of fake reviews even in the presence of fake helpfulness ratings.

$$AverageHelpfulness(IR) = \frac{1}{|IR|} \sum_{(u,i) \in IR} helpfulness(u,i) \tag{6.1}$$

Prediction shift on the target items measures the average of the change in the prediction of genuine users for the attacked items before and after a shilling attack. In other words, this metric measures the degree of success of an attack. The smaller the value of this metric, the more robust the recommendation method is.

$$PredictionShift(U, V, U', V') = \frac{1}{|U^g||I^{target}|} \sum_{u \in U^g} \sum_{i \in I^{target}} (U'V')_{u,i} - (UV)_{u,i} \tag{6.2}$$

where $(U'V')_{u,i}$ is the predicted rating value of user u for item i after an attack.

Mean Average Error(MAE) on test set is the overall prediction error on ratings in the test set which contains 10% of all item ratings of original users in the dataset. MAE is commonly used to compare the predictive accuracy of recommendation algorithms. Accurate prediction yields a small MAE. We use MAE to measure the accuracy loss that is sacrificed to improve robustness.

$$MAE(U, V) = \frac{1}{|test\ set|} \sum_{R_{u,i} \in test\ \ set} |R_{u,i} - (UV)_{u,i}| \tag{6.3}$$

6.4 Results and Analysis

To answer the first question, we visualize the results of User2Vec and compare the review quality results of each measure. In this experiment, we inject fake review through attacks with 1% attack size, 0.5% filler size, and 0.5% popular size. We set the dimensions of User2Vec's feature vectors to 32. Figure 6.1 shows the results of User2Vec. We use learned users' feature vectors as the input to the visualization tool, t-SNE [24]. The users are mapped to the 2-D space. X-shaped red points represent shillers, while green square points represent genuine users. We observed that feature vectors of shillers are very close to each other, which shows User2Vec's ability to capture shillers.

We also compute the average quality of fake reviews and genuine reviews. As shown in table 6.2, the naive quality measure allows fake reviews to have a higher quality than genuine reviews, whereas our quality measure yields the opposite. In specific, while the naive quality measure computes the quality of fake reviews at a value close to hr_{max}, our quality measure computes the quality of fake reviews at a value close to the default quality $Q_{default}$. In other words, our quality measure can prevent fake helpfulness ratings from increasing the quality of fake reviews. We observed a slight decrease in the quality

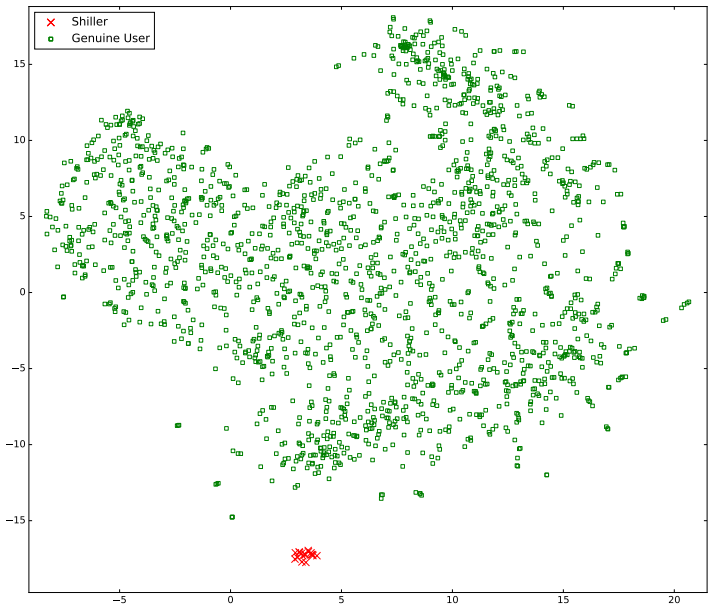


Figure 6.1: Visualization of the User2Vec result

of genuine reviews when using our method. The reason for this is that the feature vector of a genuine user might be very similar to that of another genuine user by coincidence, which leads to false positive detection. However, since the probability that false positive detection happens is very low, wrongly sacrificed genuine helpfulness ratings have no significant impact on estimating review quality. Hence, our quality measure shows its ability to estimate the true quality of reviews.

Table 6.2: Review helpfulness results. The range of helpfulness is from 0 to 5.

Attack Size	Naïve Quality Measure		Our Quality Measure	
	Fake Reviews	Genuine Reviews	Fake Reviews	Genuine Reviews
1%	5.0	3.5388	2.5	3.45

To answer the second question, we compute the prediction shift on the target items under attacks in the variety of attack sizes, filler sizes, and popular sizes. From Table 6.3, we observe that our model leads to the lowest prediction shift on the target items in all conditions. For the attack with 1% attack size, 1% filler size, and 0% popular size, our model is almost 20 times more robust than Naive WMF. The reason for this is that fake item ratings have the least impact on prediction when applying our quality

measure. We observe that the naive quality measure causes larger prediction shift on the target items than MF in the presence of fake helpfulness ratings because fake helpfulness ratings increase the influence of fake item ratings on prediction when applying the naive quality measure than when ignoring review quality. Therefore we argue that our method is resistant to review quality manipulations.

Table 6.3: Prediction shift on the target items.

Attack size	**Filler Size**	**Popular Size**	**MF**	**Naive WMF**	**Robust WMF**
1%	1%	0%	1.01465	1.7805	**0.092686**
	0.5%	0.5%	1.48154	1.90081	**0.239489**
	0%	1%	1.72337	1.79765	**0.246163**
2%	1%	0%	1.5178	2.28872	**0.172815**
	0.5%	0.5%	1.91454	2.30772	**0.387328**
	0%	1%	2.08557	2.1092	**0.469354**
3%	1%	0%	1.79902	2.5618	**0.307992**
	0.5%	0.5%	1.89458	2.49592	**0.580003**
	0%	1%	1.99723	2.24161	**0.659305**

To answer the final question, we investigate the predictive performance of each method. We compute MAE on the test set. According to 6.4, MF performs better than WMFs. In fact, MAE is not the ideal metric to measure the predictive performance of WMF, because MAE gives equal importance to the errors of all the ratings in the test set. Even though MAE is not the proper metric for WMF, MAE results of WMF are not significantly different from those of MF. We compute Cohen's d [23] for the effect size based on means of predictive errors between MF and WMF using our quality measure. The value of Cohen's d is near 0.02. And this value corresponds to a small value according to [23], which means that the difference between the two results is not significant. Consequently, we conclude that WMF using our quality measure obtain robustness at a not significant additional cost of predictive accuracy.

Table 6.4: MAE on test set.

Attack Size	**Filler Size**	**Popular Size**	**MF**	**Naive WMF**	**Robust WMF**
1%	1%	0%	**0.821944**	0.831673	0.843252
	0.5%	0.5%	**0.825909**	0.836473	0.842159
	0%	1%	**0.825078**	0.837706	0.84074
2%	1%	0%	**0.820305**	0.826343	0.840074
	0.5%	0.5%	**0.826043**	0.834851	0.836148
	0%	1%	**0.822775**	0.847235	0.843203
3%	1%	0%	**0.816267**	0.828714	0.840653
	0.5%	0.5%	**0.825463**	0.846773	0.841859
	0%	1%	**0.829685**	0.85275	0.841454

Chapter 7. Conclusion

Recommendation systems should tackle fake reviews to ensure that user experience is not compromised. Several recommendation models that take into account the quality of reviews have been proposed to yield robust recommendation results even in situations with fake reviews. However, most of the proposed models do not deal with attacks that attempt to manipulate review quality. We address the severity of these attacks and propose a robust recommendation model against review quality manipulation. We propose User2Vec and Bayesian Weighted Mean to reduce the negative effect of fake reviews and thereby obtain more robust recommendation results. Experimental results on a real-world dataset show that our model is up to 20 times more robust than the models which do not consider review quality manipulation. Future research includes developing robust models against nuke attacks and more elaborate attacks.

Bibliography

[1] M. Luca. Reviews, Reputation, and Revenue: The Case of Yelp.com. Harvard Business School Working Papers, 2011.

[2] S. Lam and J. Riedl. Shilling recommender systems for fun and profit. In Proceedings of the Thirteenth International Conference on World Wide Web. ACM, 2004.

[3] R. Burke, B. Mobasher, R. Zabicki, and R. Bhaumik. Limited knowledge shilling attacks in collaborative filtering systems. In Proceedings of the Third IJCAI Workshop in Intelligent Techniques for Personalization, 2005.

[4] R. Burke, B. Mobasher, R. Zabicki, and R. Bhaumik. Identifying attack models for secure recommendation. Beyond Personalization, 2005.

[5] R. Burke, B. Mobasher, C. Williams, and R. Bhaumik. Analysis and detection of segment-focused attacks against collaborative recommendation. 2006.

[6] Y. Koren, R. Bell, and C. Volinsky. Matrix factorization techniques for recommender systems. Computer Journal, 42, 2009.

[7] Y. Hu, Y. Koren, and C. Volinsky. Collaborative filtering for implicit feedback datasets. In Proceedings of the Eighth IEEE International Conference on Data Mining, 2008.

[8] B. Mehta, T. Hofmann, and W. Nejdl. Robust Collaborative Filtering. In Proceedings of the 1st ACM Conference on Recommender Systems, 2007.

[9] B. Mehta and W. Nejdl. Attack resistant collaborative filtering. In Proceedings of the Thirty-First Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, 2008.

[10] B. Mehta, T. Hofmann, and P. Fankhauser. Lies and propaganda: detecting spam users in collaborative filtering.Proceedings of the 12th international conference on Intelligent user interfaces, 2007.

[11] B. Mehta. Unsupervised shilling detection for collaborative filtering. In Proceedings of the Twenty-Second Conference on Artificial Intelligence. AAAI, 2007.

[12] N. Jindal and B. Liu. Opinion spam and analysis. In WSDM, 2008.

[13] J. Liu, Y. Cao, C.-Y. Lin, Y. Huang, and M. Zhou. Low-quality product review detection in opinion summarization. In EMNLP-CoNLL, 2007.

[14] M. Ott, Y. Choi, C. Cardie, and J. T. Hancock. Finding Deceptive Opinion Spam by Any Stretch of the Imagination. In ACL, 2011.

[15] S. Kim, P. Pantel, T. Chklovski, and M. Pennacchiotti. Automatically assessing review helpfulness. EMNLP, 2006.

[16] S. Raghavan, S. Gunasekar, and J. Ghosh. Review quality aware collaborative filtering. In Proceedings of the sixth ACM conference on Recommender systems, 2012.

[17] S. Wang, J. Tang, and H. Liu, Toward Dual Roles of Users in Recommender Systems, In CIKM, 2015.

[18] T. Mikolov, K. Chen, G. Corrado, and J. Dean. Efficient estimation of word representations in vector space. In ICLR, 2013.

[19] T. Mikolov, I. Sutskever, K. Chen, G. S. Corrado, and J. Dean. Distributed representations of words and phrases and their compositionality. In NIPS, 2013.

[20] B. Perozzi, R. Al-Rfou, and S. Skiena. DeepWalk: Online learning of social representations. In KDD, 2014.

[21] A. Grover and J. Leskovec. node2vec: Scalable Feature Learning for Networks. In KDD, 2016.

[22] G. Guo, J. Zhang, D. Thalmann, and N. Yorke-Smith. Etaf: An extended trust antecedents framework for trust prediction. In ASONAM, 2014.

[23] J. Cohen. Statistical Power Analysis for the Behavioral Sciences. 1988.

[24] L. Van der Maaten and G. Hinton. Visualizing data using t-sne. Journal of Machine Learning Research, 2008.

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이 논문을 작성하기까지 도움을 주신 모든 분들께 감사드립니다. 먼저 석사 과정 동안 지도해주시고 저의 여러 고민을 성심성의껏 상담해주신 이윤준 교수님께 깊은 감사의 말씀을 드립니다. 교수님의 제자로서 부끄럽지 않은 사람이 되도록 항상 노력하겠습니다. 아울러 귀한 시간을 내시어 논문을 심사해주시고 조언을 아끼지 않아 주신 김명호 교수님, 유신 교수님께도 깊은 감사 드립니다.

즐겁게 생활한 데이터베이스 연구실 사람들에게도 감사의 마음을 전합니다. 연구실 학생들을 친자식처럼 대해주시고 저희가 잘 모르는 업무를 열심히 도와주신 박경희 선생님, 랩장으로서 책임감 있게 연구실 사람들을 신경 써주시고 웃음이 많은 후영 누나, 제 말에 잘 웃어주시고 주말에도 연구실에 나와서 열심히 연구하던 수형이형, 컴퓨터 장비 관련 문제를 도와주신 똑똑한 우람이형, 프로젝트도 같이 하고 삶의 여러 지혜를 전수하시고 저의 디펜스도 열심히 도와주신 민호형, 백과사전같이 다방면으로 아는 것이 많고 공감대 형성이 잘 되어 재밌던 창욱이형, 연구실의 분위기를 담당한 화진누나, 연구실 일을 항상 묵묵히 잘 해내고 여러모로 도와주는 대인배 남윤이, 더 같이 지내지 못해 아쉬운 원영이형에게도 감사의 마음을 전합니다. 데이터베이스 연구실 가족이 되어 정말 행복한 대학원 생활을 할 수 있었습니다.

그리고 기쁜 일과 슬픈 일을 함께한 석사 동기들과 친구들에게도 감사의 인사를 드립니다. 앞으로도 함께하는 시간을 많이 가질 수 있길 희망하고 하고자 하는 일 모두 잘 되길 응원하겠습니다.

마지막으로 항상 절 지지해주시는 사랑하는 가족들에게도 감사드립니다. 지금의 제가 있을 수 있도록 길러주시고 베풀어주셔서 감사합니다. 앞으로도 멋진 모습을 보여드리며 은혜에 보답하도록 하겠습니다.

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