Can Reputation Manipulation Boost App sales in Android Market?

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***Abstract*—With the big success of the mobile application (app) sales, attackers are also attracted by the potential profits in the app market. In this paper, we survey current app ranking schemes as well as existing app reputation manipulation schemes and raise some interesting while arguable questions. Based on an app installation data set collected from a university campus community, we quantitatively investigate the answers to two questions: (1) what is the impact of app reputation and download number on app sales and (2) will attackers make profits from the manipulation of app reputation or download number. Although the results may not be generalized to the global app market, they provide a new view point for further investigations.**

I. Introduction

With the wide spread of smart phones and tablet computers, the sale of mobile applications is experiencing an overwhelming growth. In June 2012, Apple's app store has hit the 30 billion downloads milestone. Accompanied with this, other companies, such as Google, Amazon, blackberry, have also opened their own app markets and are achieving big success. The app markets have provided unique opportunities for big companies, small businesses, and independent developers to gain enormous profit. A success story is that Steve Demeter, an independent developer, has made $250,000 in just two months by his $5 app "Trism" [1].

Numerous web pages, blogs, forums, and books have joined in the heated discussion about how to increase app sales, and diverse app boosting strategies are proposed [2]–[5]. Researchers are also attracted to investigate the various factors that influence the app download [6], generating knowledge that helps the fundamental understanding of app markets.

Among these discussions and research, app reputation (i.e. users' rating values to apps) and download number are widely acknowledged as important factors in influencing users' app installation decisions. However, limited research has been done to quantitatively evaluate the impact of reputation and download number on app sales.

Furthermore, in the e-commerce websites, where reputation schemes are widely adopted today, different attack strategies are discovered to make profit by manipulating online items' reputation or purchasing number. There is ample evidence showing that firms post biased ratings and reviews to praise their own products or badmouth their competitors' products. There are even scammers making profit by writing sophisticated programs to automatically insert ratings [7]. It seems that these manipulations can also be effective in the app market. However, different from other e-commerce websites, the app market has its unique features.

- Reputation or download number is not the only factor to judge the quality of an app. For example, App markets provide app rank charts, where the top ranked apps are more likely to be installed by users. Furthermore, with the rapid development of the mobile market, tremendous of users have experiences of installing mobile apps. In this scenario, users are more often to share their app installations with their friends or social connections. In other words, social factors also play important roles in influencing users' app installation decisions.
- In the app market, users can provide ratings to an app only if they have installed this app. And app markets will take a certain percentage of the revenue, for example 30%, from app sellers. It indicates that attackers cannot arbitrarily generate dishonest ratings to apps unless they pay for the cost (e.g. 30% of the app price).

These specific features make the feasibility of reputation manipulation in app market ambiguous.

In this paper, we aim to answer two questions. (1) What is the impact of app reputation and download number on app sales? (2) Will attackers make profits from the manipulation of app reputation or download number?

The rest of the paper is organized as follows. We first conduct a survey on app ranking schemes and existing manipulations of app reputation or download number in Section II. Then, in Section III, we conduct experiments based on real user data collected from a university campus community. In the experiments, we analyze the impact of app reputation and download number on app sales and the effectiveness of manipulations. Finally, we summarize our findings and discuss their implications in Section IV.

II. Survey of App Ranking Schemes and Existing Manipulations

In this section, we conduct survey for app ranking schemes and existing manipulations on app reputation and download number. It is important to point out that limited researches [2], [3], [6] have been performed in this area. Therefore, we collect opinions not only from research literatures, but also from online articles as well as discussion forums.

A. App Ranking Schemes

As discussed in Section I, app rank plays an important role in influencing app sales. Let's first look at how app markets rank their apps.

Before April, 2011, people believed that Apple determined app rankings purely based on the download number. Then Apple has changed its ranking algorithm by considering more factors other than just download number. People believe that some qualitative information, such as ratings and frequency of usage, is taken into consideration. Different from Apple app store, Android market employs more complex ranking algorithms which considers app download number, retention rate, usage frequency, rating values, number of ratings, installing/uninstalling rate and etc. [8].

By comparing these two different app markets, we find out that in both markets, (1) **download number** is the most important factor in determining app rankings; and (2) **ratings and reviews** start to play more important roles in influencing app rankings. However, these two factors are not the only factors considered by app ranking schemes.

B. Manipulations of App Reputation and Download Number

Numerous advices and tricks on how to obtain positive ratings and reviews are prevalent. For example, send positive ratings to app store while get negative feedback coming to the developers [2]; ask for ratings after several usages by assuming that users who do not like the app will quit using it after 1∼2 usage [3]; or conduct frequent app updates to drive more positive ratings and reviews [3]. These suggestions may help a specific app to gain more positive ratings and reviews. However, they can hardly generate large scale manipulations on the app market.

More advanced manipulations on app reputation and download number do exist. To manipulate the app download number, one well known way is the pay-per-install model, where app developers pay for each install to drive the download number [9]. There are usually two ways of pay-per-install. First, some companies, such as Tapjoy [10] and Flurry [11], provide pay-per-install networks composed by plenty of apps. Once your app joins in this network, its download number will be dramatically promoted by other apps in the network. For example, some apps encourage their users through virtual currency or level upgrading to download your app. Once your app has been installed due to this promotion, you will pay the company (e.g. Tapjoy, Flurry) and the apps that generate this install. Second, some companies, such as App Lifter [12], provide services for app developers to directly pay users for installing their apps. Usually the users will be paid a little bit higher than the app price [13]. The same companies that help the developers increase the number of downloads can surely help insert positive ratings and reviews.

Remaining Questions: All these examples above clearly show that people believe increasing positive ratings/reviews and download number as powerful app promotion techniques. However, **are these techniques always effective? Does their effectiveness justify their cost?** In Section III, we will describe a quantitative study on app downloading behaviors in a very special community: university campus. The results for this special community may not be generalized to a broader consumer base, but will yield some interesting insights.

III. Experiment and Result

During the survey in Section II, we have raised some questions which are not well solved by current literatures. To answer these remaining questions, in this section, we conduct experiments on a real user data set collected from a university campus community. We aim to understand, for this university campus community, whether the manipulation of the app reputation or download number can significantly affect app sales. Some interesting results have been obtained.

A. Testing Data Set

We use a real user data set collected by MIT Media lab [6] as the testing data set. This data set, collected from March to July 2010, recorded the installations of 821 apps from 55 participants who were residents living in a graduate student residency of a major US university. In this data set, the following information has been collected.

- App related information, such as *app name*, *prices*, *ratings* and global *download number*.
- User related information.
  - Users' *app installation* information (i.e. which user installed which app at what time).
  - *Call log* and *bluetooth hits* information. During the data collection period, each participant was given an Android-based cell phone with a built-in sensing software to capture all call logs and bluetooth hits among the given phones. Call logs were used to indicate participants' interactions through phone calls. Bluetooth hits recorded participants' face-to-face interactions, during which the phones were within each other's vicinity. These two types of information described participants' daily interactions.
  - Users' *friendship*, *affiliation* and *race* information was also collected through a survey. In the survey, each participant provided his/her affiliation and race, and rated his/her friendship relationship to other participants. Such information reflected more about participants' long term relationship.

This data set is **unique** and fulfill our requirements due to two reasons. (1) It contains both app related information and user related information. Most of the current data collections focus on the app related information, whereas the lack of user related information makes it difficult to analyze the underlying reasons for a user to install a specific app. (2) It contains rich information about users' offline social behaviors, such as phone calls, face-to-face interactions or friendship in real life. These offline information, which is seldom included in other data collections, may significantly affect users' app installation decisions.

Using this data set, we can verify that, in the university campus community, whether the app reputation and download number have impact on app sales and furthermore, whether the manipulation of these two factors will gain profit. The results obtained may be applied to other closely connected social communities, but may not be applicable to everyone.

B. Manipulations of Rating and Download Number

As presented in Section II, ratings and download number are two important factors influencing app sales. It is widely believed that the installations of an app can be greatly boosted by an increase in its rating values or download number. Therefore, many companies provide diverse app promotion services by manipulating app ratings or download number. In this section, we focus on the pay-per-install manipulation mentioned in Section II. Compared with the attacks against rating systems in general (e.g. Amazon product rating systems), the manipulation of the rating system in the app market is easier to analyze, for two reasons.

- In order to insert an unfair rating or increase the download number of an app, attackers have to buy this app. If the attacker is the seller of the app, he/she still needs to pay for the app markets' share of the revenue, which is usually 30% of the app price. If the attacker is a user in the pay-per-install network, the seller of the app needs to pay a fee higher than the app price. Therefore, the cost of such manipulation can be calculated. In this work, we assume the *cost of manipulation* is $x\%$ of the revenue.
- Normal users cannot "return" the apps that they have purchased, even if they are misled by false ratings or false app descriptions. It makes securing the rating system in app

	Possible **Inputs** to the Prediction Model	Data Source
I_1	Call Log	Dataset used in [6]
I_2	Bluetooth Hit	Dataset used in [6]
I_3	Friendship	Dataset used in [6]
I_4	Affiliation	Dataset used in [6]
I_5	Race	Dataset used in [6]
I_6	Number of Download in the app Market	Collected from the App Market
I_7	Rating Score (5 star scale)	Collected from the App Market

TABLE I: Information for Predicting App Downloads

markets very important. Furthermore, it leads to an easier estimation of the *gain of the manipulation*, as we will show later in this section.

These two distinct features provide us an opportunity to evaluate the effectiveness of app rating or download manipulations by building up the *manipulation cost/gain model*. In the next subsection, we discuss the details of the manipulation cost and gain.

1) **Manipulation Cost and Manipulation Gain:** Assume that the app price is p. To insert one rating or increase the download number by 1, the attacker needs to buy the app once. Thus, it is not hard to estimate the manipulation cost.

The challenging task is to estimate the manipulation gain. We need to estimate how many more installations will occur if the existing rating value or the existing download number increases by a certain amount. For each new installation, the manipulation gain can be calculated as $p(1-x\%)$, where $x\%$ is the revenue share taken by the app market. The value of $x\%$ is about 0.3 in the current App market. This estimation is challenging since there is not a perfect way to predict app installations. To handle this issue, we apply the prediction model proposed in [6], which predicts app installations by constructing a composite network containing multiple sources of information. When compared with other models, this prediction model yields a significantly higher prediction accuracy. To our best knowledge, this is currently the best model in terms of predicting app installations considering social factors. Therefore, we adopt this prediction model as the base to investigate the manipulation gain.

In [6], the prediction model considered users' social information within the community, as discussed in Section III-A. In this paper, we introduce app rating and download number as additional input information to the original prediction model. Thus, all possible factors that can be used to predict app download numbers are shown in Table I.

In [6], the goal is to derive the optimized model to combine all the input information so that users' app installation decisions can be predicted with the highest accuracy. The **output** of this optimized prediction model is the most accurate prediction probability about whether a given user k will install a specific app a. This probability is denoted as $P_a(k)$. Note that the user k needs to be one of the 55 participants in the study. The details can be found in [6].

For a given app a, we use the prediction model to calculate the impact of rating or download number as follows.

1 Optimizing the parameters of the prediction model. We use all available data (i.e. information $I_1 \sim I_7$ for all participants, as well as the apps they have installed) to train the prediction model. Note that, the rating and download number for a given app may change as time goes by. However, we argue that such changes do not have big influence in the training process. The download number that we used for training is a rough range, such as 50,000 $\sim$ 100,000, or 100,000$\sim$ 200,000. Since the data collection process only lasted for 4 months, for a given app, its the download number was roughly in the same range. Regarding to the app ratings, since all of these apps were not new apps, we consider that the rating values were converged already and not changing rapidly during the experiment period.

2 Calculating download probability before manipulation. For a given app a, use the optimized prediction model to predict the probability that user k installs the app. This probability is denoted by $P_a(k)^{org}$. The input of the prediction model is the information of user k (i.e. $I_1 \sim I_5$) and the information of app a (i.e. I_6 and I_7). This calculation is performed for all 55 users.

3 Adjusting the app information, as if manipulation has occurred. If we study the impact of app rating, we increase the app rating value (i.e. I_7) by a certain amount. If we study the impact of the download number, we increase the download number (i.e I_6) by a certain amount.

4 Calculating download probability after manipulation. Use the user information and the adjusted app information to predict the download number of app a. Let $P_a(k)^{adj}$ denote the probability that user k will download app a after the adjustment of app information. Obliviously, $P_a(k)^{adj}$ should be no less than $P_a(k)^{org}$.

5 Computing the total download increase. The total download increase for app a due to the manipulation, denoted by M_a^{inc} is calculated as

$$M_a^{inc} = \sum_{k=1}^{N} (P_a(k)^{adj} - P_a(k)^{org}),$$

where $N = 55$.

2) **Impact of Rating Value Increase:** Among the 821 apps collected in the data set, 5 apps are preset in the Android phones. Besides these 5 apps, only 273 apps have been installed by at least two users. In the discussions below, we just consider these 273 apps. To train the optimized prediction model, we construct the composite network by considering the information I_1, I_2, I_3, I_4, I_7 in Table I. Except rating values, the other four types of information were proved to be influential factors in predicting app installations [6].

Figure 1 demonstrates that for each specific app, when we increase the app rating value by a certain amount, how many more installations will be triggered. In Figure 1, the x axis represents the app index, and y axis represents the installation probability increment. The rating information used for prediction is the raw rating value ranging from 1 to 5. Figure 1 is obtained by increasing the rating value of each app by 1.

From Figure 1, we can observe that for each app, when the rating value increases by 1, the installation probability also increases. However, the installation probability increase value is very small, around 10^{-10}.

If we manipulate the ratings to different values, how will the app installations change? In Figure 2, we demonstrate the relationship between the app installation probability change and the rating value change.

In Figure2, the x axis represents rating increment value ranging from -1 to 1 and the y axis represent the app installation

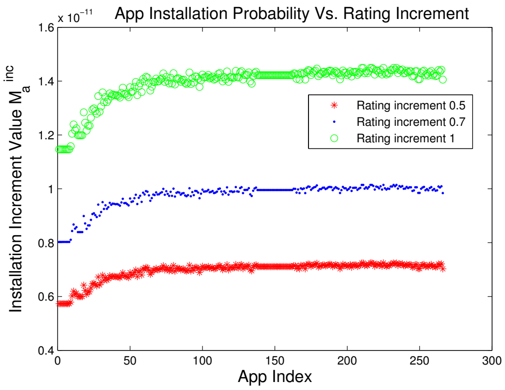

Fig. 1: App Installation Probability Increment Vs Rating Increment.

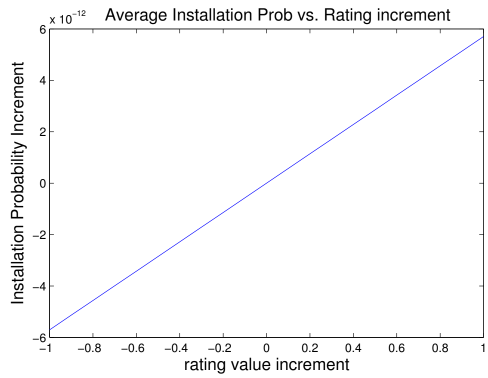

Fig. 2: Impact of Rating Value Change on App Installation Probability

probability increment value. Figure 2 is generated by repeatedly changing the rating value. From Figure 2, we can observe that (1) the relationship between the rating information and installation probability is actually a linear curve, meaning that the installation probability monotonically increases with the rating value increase; and (2) when the rating value is increased by 1, the average installation probability increment is only about $1.5 * 10^{-11}$, which is negligible. It indicates that *for a closely connected community, the global rating information has trivial impact on influencing users' app installations*. The possible reason is that in such kind of community, instead of global rating information, users could refer to their friends, colleges or family members for app installation recommendations. In other words, the local app "rating" information, which is reflected by installations from a users' local connections, overwrites the global rating information, and has significantly influenced users' app installation decisions.

3) **Impact of Download Number Increase:** Similarly, we trained the prediction model to investigate the impact of current app download number on the future app installations. To train the optimized prediction model, we construct the composite network by considering the information I_1, I_2, I_3, I_4, I_6 in Table I.

In Figure3, the x axis represents the downloading increase value, ranging from 0 to 10^6 and the y axis represent the app installation probability increment value. Figure 3 is generated by repeatedly changing the download number value. From Figure 3, we can observe that (1) the relationship between the download number and installation probability is also a linear curve, meaning

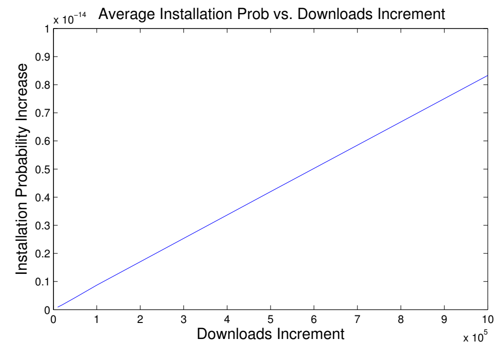

Fig. 3: Impact of Download Number Value Change on App Installation Probability

that the installation probability monotonically increases with the download number increase; and (2) when the download number increase by 10^6, the installation probability increment is only about $0.85 * 10^{-14}$, which is negligible. Similarly, *for a closely connected community, the global download information does not have an obvious impact either*. The possible reason is that when users have closely connected friends, colleges or family members to obtain app installation suggestions, the global app download information is not important any longer.

As a summary, Figure 2 and 3 demonstrate the impact of apps' rating information and download number on users' app installation decisions. Unfortunately, the value change of these two factors will not affect users' decision too much. Recall that in Section II, we discuss that some companies provide promotion services by manipulating apps' rating information or download number. Based on our experiment results, this type of manipulation is definitely not a good choice. Note that, our data is a university campus community data, where local contacts (e.g. call log, friendship, and etc) may dominate users' installation decision. And these results may not be able to apply directly on other type of user communities. However, we do provide a way to estimate the cost and gain of the rating and download number manipulation strategies. The app developers who plan to promote their app sales through the rating and download number manipulations need to reconsider its effectiveness carefully.

IV. Conclusion

In this work, we survey current popular strategies for manipulating app reputation and download number. Furthermore, based on a real user data collected from a university campus community, we quantitatively evaluate the impact of app rating and download number on users' app installation decisions. The results have answered the two questions raised in Section I. (1) App reputation and download number have limited impact on users' installation decisions. (2) Attack strategies which boost app sales by manipulating app reputation and download number will have their cost much higher than the profit. These results are particularly helpful for app developers who want to promote the apps designed for special interest groups or special communities.

However, this work has its own limitation. In particular, the participants in this experiment have formed a university campus community. This type of community may have much more close contacts among its members than other type of communities do. Therefore these results may not be generalized to the global app market. However, they provide a new view point for further investigations.

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