

A Innovative Approach to Discovery of Ranking Fraud for Mobile Apps

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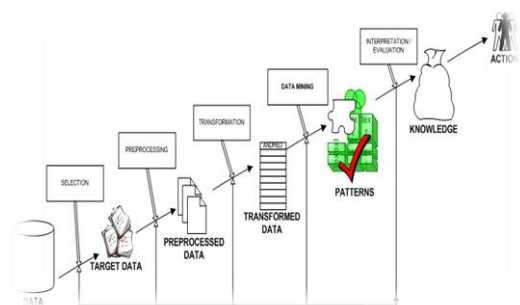
ABSTRACT:

Ranking fraud in the mobile App market refers to fraudulent or deceptive activities which have a purpose of bumping up the Apps in the popularity list. Indeed, it becomes more and more frequent for App developers to use shady means, such as inflating their Apps' sales or posting phony App ratings, to commit ranking fraud. While the importance of preventing ranking fraud has been widely recognized, there is limited understanding and research in this area. To this end, in this paper, we provide a holistic view of ranking fraud and propose a ranking fraud detection system for mobile Apps. Specifically, we first propose to accurately locate the ranking fraud by mining the active periods, namely leading sessions, of mobile Apps. Such leading sessions can be leveraged for detecting the local anomaly instead of global anomaly of App rankings.

Furthermore, we investigate three types of evidences, i.e., ranking based evidences, rating based evidences and review based evidences, by modeling Apps' ranking, rating and review behaviors through statistical hypotheses tests. In addition, we propose an optimization based aggregation method to integrate all the evidences for fraud detection. Finally, we evaluate the proposed system with real-world App data collected from the iOS App Store for a long time period. In the experiments, we validate the effectiveness of the proposed system, and show the scalability of the detection algorithm as well as some regularity of ranking fraud activities.

INTRODUCTION

What is Data Mining?



Structure of Data Mining

Generally, data mining (sometimes called data or knowledge discovery) is the process of analyzing data from different perspectives and summarizing it into useful information - information that can be used to increase revenue, cuts costs, or both. Data mining software is one of a number of analytical tools for analyzing data. It allows users to analyze data from many different dimensions or angles, categorize it, and summarize the relationships identified. Technically, data mining is the process of finding correlations or patterns among dozens of fields in large relational databases.

How Data Mining Works?

While large-scale information technology has been evolving separate transaction and analytical systems, data mining provides the link between the two. Data mining software analyzes relationships and patterns in stored transaction data based on open-ended user queries.

Several types of analytical software are available: statistical, machine learning, and neural networks.

Generally, any of four types of relationships are sought:

Classes: Stored data is used to locate data in predetermined groups. For example, a restaurant chain could mine customer purchase data to determine when customers visit and what they typically order. This information could be used to increase traffic by having daily specials.

Clusters: Data items are grouped according to logical relationships or consumer preferences. For example, data can be mined to identify market segments or consumer affinities.

Associations: Data can be mined to identify associations. The beer-diaper example is an example of associative mining.

Sequential patterns: Data is mined to anticipate behavior patterns and trends. For example, an outdoor equipment retailer could predict the likelihood of a backpack being purchased based on a consumer's purchase of sleeping bags and hiking shoes.

Data mining consists of five major elements:

1. Extract, transform, and load transaction data onto the data warehouse system.
2. Store and manage the data in a multidimensional database system.
3. Provide data access to business analysts and information technology professionals.
4. Analyze the data by application software.
5. Present the data in a useful format, such as a graph or table.

EXISTING SYSTEM:

- ❖ In the literature, while there are some related work, such as web ranking spam detection, online review spam detection and mobile App recommendation,

the problem of detecting ranking fraud for mobile Apps is still under-explored.

- ❖ Generally speaking, the related works of this study can be grouped into three categories.
- ❖ The first category is about web ranking spam detection.
- ❖ The second category is focused on detecting online review spam.
- ❖ Finally, the third category includes the studies on mobile App recommendation

DISADVANTAGES OF EXISTING SYSTEM:

- ❖ Although some of the existing approaches can be used for anomaly detection from historical rating and review records, they are not able to extract fraud evidences for a given time period (i.e., leading session).
- ❖ Cannot able to detect ranking fraud happened in Apps' historical leading sessions
- ❖ There is no existing benchmark to decide which leading sessions or Apps really contain ranking fraud.

PROPOSED SYSTEM:

- ❖ We first propose a simple yet effective algorithm to identify the leading sessions of each App based on its historical ranking records. Then, with the analysis of Apps' ranking behaviors, we find that the fraudulent Apps often have different ranking patterns in each leading session compared with normal Apps. Thus, we characterize some fraud evidences from Apps' historical ranking records, and develop three functions to extract such ranking based fraud evidences.
- ❖ We further propose two types of fraud evidences based on Apps' rating and review history, which reflect some anomaly patterns from Apps' historical rating and review records.
- ❖ In Ranking Based Evidences, by analyzing the Apps' historical ranking records, we observe that Apps' ranking behaviors in a leading event always satisfy a specific ranking pattern, which consists of

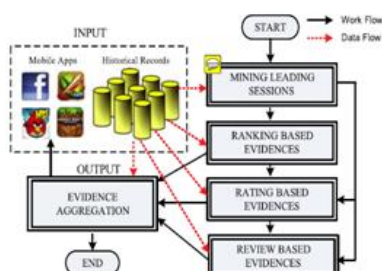
three different ranking phases, namely, rising phase, maintaining phase and recession phase.

- ❖ In Rating Based Evidences, specifically, after an App has been published, it can be rated by any user who downloaded it. Indeed, user rating is one of the most important features of App advertisement. An App which has higher rating may attract more users to download and can also be ranked higher in the leaderboard. Thus, rating manipulation is also an important perspective of ranking fraud.
- ❖ In Review Based Evidences, besides ratings, most of the App stores also allow users to write some textual comments as App reviews. Such reviews can reflect the personal perceptions and usage experiences of existing users for particular mobile Apps. Indeed, review manipulation is one of the most important perspective of App ranking fraud.

ADVANTAGES OF PROPOSED SYSTEM:

- ❖ The proposed framework is scalable and can be extended with other domain generated evidences for ranking fraud detection.
- ❖ Experimental results show the effectiveness of the proposed system, the scalability of the detection algorithm as well as some regularity of ranking fraud activities.
- ❖ To the best of our knowledge, there is no existing benchmark to decide which leading sessions or Apps really contain ranking fraud. Thus, we develop four intuitive baselines and invite five human evaluators to validate the effectiveness of our approach Evidence Aggregation based Ranking Fraud Detection (EA-RFD).

SYSTEM ARCHITECTURE:



IMPLEMENTATION

MODULES:

- Mining Leading Sessions
- Ranking Based Evidences
- Rating Based Evidences
- Review Based Evidences
- Evidence Aggregation

MODULES DESCRIPTION

Mining Leading Sessions

In the first module, we develop our system environment with the details of App like an app store. Intuitively, the leading sessions of a mobile App represent its periods of popularity, so the ranking manipulation will only take place in these leading sessions. Therefore, the problem of detecting ranking fraud is to detect fraudulent leading sessions. Along this line, the first task is how to mine the leading sessions of a mobile App from its historical ranking records. There are two main steps for mining leading sessions. First, we need to discover leading events from the App's historical ranking records. Second, we need to merge adjacent leading events for constructing leading sessions.

Ranking Based Evidences

In this module, we develop Ranking based Evidences system. By analyzing the Apps' historical ranking records, we serve that Apps' ranking behaviors in a leading event always satisfy a specific ranking pattern, which consists of three different ranking phases, namely, rising phase, maintaining phase and recession phase. Specifically, in each leading event, an App's ranking first increases to a peak position in the leaderboard (i.e., rising phase), then keeps such peak position for a period (i.e., maintaining phase), and finally decreases till the end of the event (i.e., recession phase).

Rating Based Evidences

In the third module, we enhance the system with Rating based evidences module.

The ranking based evidences are useful for ranking fraud detection. However, sometimes, it is not sufficient to only use ranking based evidences. For example, some Apps created by the famous developers, such as Gameloft, may have some leading events with large values of u1 due to the developers' credibility and the "word-of-mouth" advertising effect. Moreover, some of the legal marketing services, such as "limited-time discount", may also result in significant ranking based evidences. To solve this issue, we also study how to extract fraud evidences from Apps' historical rating records.

Review Based Evidences

In this module we add the Review based Evidences module in our system. Besides ratings, most of the App stores also allow users to write some textual comments as App reviews. Such reviews can reflect the personal perceptions and usage experiences of existing users for particular mobile Apps. Indeed, review manipulation is one of the most important perspective of App ranking fraud. Specifically, before downloading or purchasing a new mobile App, users often first read its historical reviews to ease their decision making, and a mobile App contains more positive reviews may attract more users to download. Therefore, imposters often post fake reviews in the leading sessions of a specific App in order to inflate the App downloads, and thus propel the App's ranking position in the leader board.

Evidence Aggregation

In this module we develop the Evidence Aggregation module to our system. After extracting three types of fraud evidences, the next challenge is how to combine them for ranking fraud detection. Indeed, there are many ranking and evidence aggregation methods in the literature, such as permutation based models score based models and Dempster-Shafer rules. However, some of these methods focus on learning a global ranking for all candidates. This is not proper for detecting ranking fraud for new Apps. Other methods are based on supervised learning techniques, which depend on the labeled training data and are hard to be

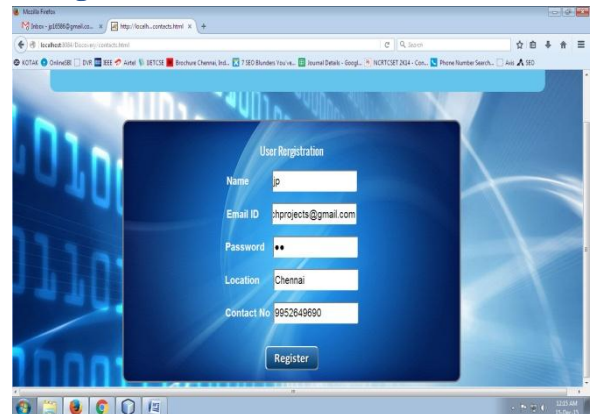
exploited. Instead, we propose an unsupervised approach based on fraud similarity to combine these evidences.

SCREEN SHOTS

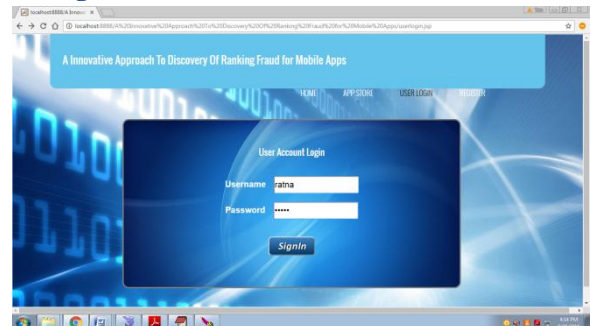
Home:



User Registration:



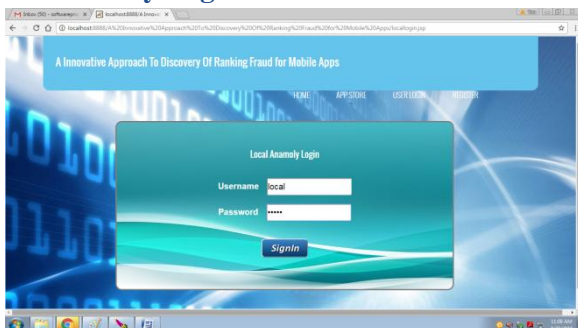
User Login:



Global Anomaly Login:



Local Anomaly Login:



CONCLUSION

In this paper, we developed a ranking fraud detection system for mobile Apps. Specifically, we first showed that ranking fraud happened in leading sessions and provided a method for mining leading sessions for each App from its historical ranking records. Then, we identified ranking based evidences, rating based evidences and review based evidences for detecting ranking fraud. Moreover, we proposed an optimization based aggregation method to integrate all the evidences for evaluating the credibility of leading sessions from mobile Apps. An unique perspective of this approach is that all the evidences can be modeled by statistical hypothesis tests, thus it is easy to be extended with other evidences from domain knowledge to detect ranking fraud. Finally, we validate the proposed system with extensive experiments on real-world App data collected from the Apple's App store.

Experimental results showed the effectiveness of the proposed approach. In the future, we plan to study more effective fraud evidences and analyze the latent

relationship among rating, review and rankings. Moreover, we will extend our ranking fraud detection approach with other mobile App related services, such as mobile Apps recommendation, for enhancing user experience.

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