International Journal of Research
Available at https://edupediapublications.org/journals
p-ISSN: 2348-6848
e-ISSN: 2348-795X
Volume 03 Issue 13
September 2016

Discovery of Ranking Fraud for Mobile Apps for bumping up the Apps

#1 SHAIK HUSSAIN SHARIF, #2YONAS ABATE DEBALKI,

Dept of Information Technology

KOMBOLCHA INSTITUTE OF ENGINEERING AND TECHNOLOGY, WOLLO UNIVERSITY, KOMBOLCHA, ETHIOPIA.

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.

1 INTRODUCTION: THE number of mobile Apps has grown at a breathtaking rate over the past few years. For example, as of the end of April 2013, there are more than 1.6 million Apps at Apple's App store and Google Play. To stimulate the development of mobile Apps, many App stores launched daily App leaderboards, which demonstrate the chart rankings of most popular Apps. Indeed, the App leaderboard is one of the most important ways for promoting mobile Apps. A higher rank on the leaderboard usually leads to a huge number of downloads and million dollars in revenue. Therefore, App developers tend to explore various ways such as advertising campaigns to promote their Apps in order to have their Apps ranked as high as possible in such App leaderboards. However, as a recent trend, instead of relying on traditional marketing solutions, shady App developers resort to some fraudulent means to deliberately boost their Apps and eventually manipulate the chart rankings on an App store. This is usually implemented by using so-called "bot farms" or "human water armies" to inflate the App downloads, ratings and reviews in a very short time. For example, an article from VentureBeat [4] reported that, when an App was promoted with the help of ranking manipulation, it could be propelled from number 1,800 to the top 25 in Apple's top free leaderboard and more than 50,000-100,000 new users could be acquired within a couple of days. In fact, such ranking fraud raises great concerns to the mobile App

industry. For example, Apple has warned of cracking down on App developers who commit ranking fraud [3] in the Apple's App store. In the literature, while there are some related work, such as web ranking spam detection [22], [25], [30], online review spam detection [19], [27], [28], and mobile App recommendation [24], [29], [31], [32], the problem of detecting ranking fraud for mobile Apps is still under-explored. To fill this crucial void, in this paper, we propose to develop a ranking fraud detection system for mobile Apps. Along this line, we identify several important challenges.

First, ranking fraud does not always happen in the whole life cycle of an App, so we need to detect the time when fraud happens. Such challenge can be regarded as detecting the local anomaly instead of global anomaly of mobile Apps. Second, due to the huge number of mobile Apps, it is difficult to manually label ranking fraud for each App, so it is important to have a scalable way to automatically detect ranking fraud without using any benchmark information. Finally, due to the dynamic nature of chart rankings, it is not easy to identify and confirm the evidences linked to ranking fraud, which motivates us to discover some implicit fraud patterns of mobile Apps as evidences. Indeed, our careful observation reveals that mobile Apps are not always ranked high in the leaderboard, but only in some leading events, which form different leading sessions. Note that we will introduce both leading events and leading sessions in detail later. In other words, ranking fraud usually happens in these leading sessions. Therefore, detecting ranking fraud of mobile Apps is actually to detect ranking fraud within leading sessions of mobile Apps. Specifically, 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. Nonetheless, the ranking based evidences can be affected by App developers' reputation and some legitimate marketing campaigns, such as "limited-time discount". As a result, it is not sufficient to only use ranking based evidences. Therefore, 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 addition, we develop an unsupervised evidence-aggregation method to integrate these three types of evidences for evaluating the credibility of leading sessions from mobile Apps. Fig. 1 shows the framework of our ranking fraud detection system for mobile Apps. It is worth noting that all the evidences are extracted by modeling Apps' ranking, rating and review behaviors through statistical hypotheses tests. The proposed framework is scalable and can be extended with other domaingenerated evidences for ranking fraud detection. Finally, we evaluate the proposed system with real-world App data collected from the Apple's App store for a long time period, i.e., more than two years. Experimental results show the effectiveness of the proposed system, the scalability of the detection algorithm as well as some regularity of ranking fraud activities. Overview. The remainder of this paper is organized as follows. In Section 2, we introduce some preliminaries and how to mine leading sessions for mobile Apps. Section 3 presents how to extract ranking, rating and review based evidences and combine them for ranking fraud detection. In Section 4 we make some further discussion about the proposed approach. In Section 5,

we report the experimental results on two long-term real-world data sets. Section 6 provides a brief review of related works. Finally, in Section 7, we conclude the paper and propose some future research directions.

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, web 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.

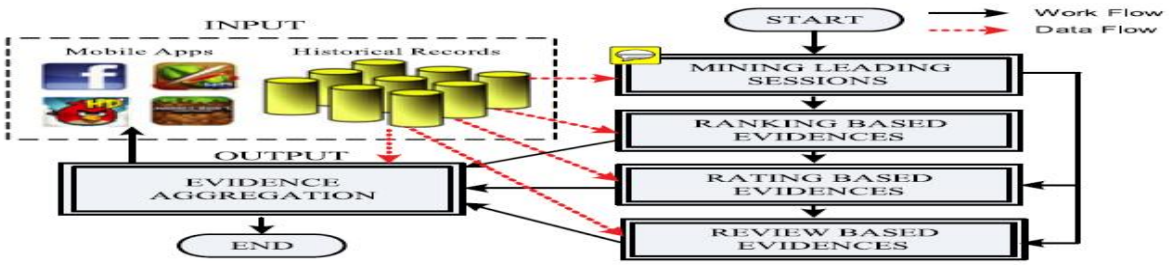
Evidence Aggregation

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.

SYSTEM DESIGN

SYSTEM ARCHITECTURE:

International Journal of Research
Available at https://edupediapublications.org/journals
p-ISSN: 2348-6848
e-ISSN: 2348-795X
Volume 03 Issue 13
September 2016

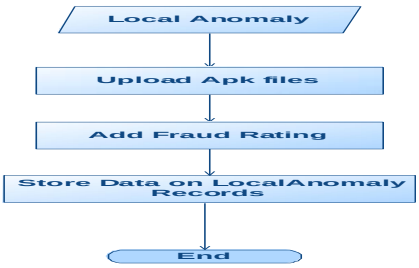


DATA FLOW DIAGRAM:

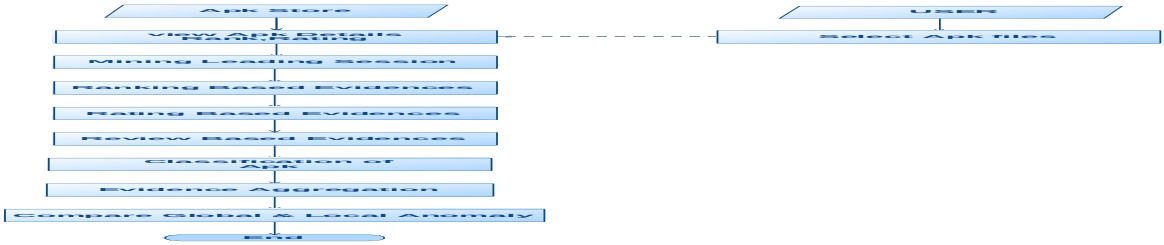
1. The DFD is also called as bubble chart. It is a simple graphical formalism that can be used to represent a system in terms of input data to the system, various processing carried out on this data, and the output data is generated by this system.
2. The data flow diagram (DFD) is one of the most important modeling tools. It is used to model the system components. These components are the system process, the data used by the process, an external entity that interacts with the system and the information flows in the system.
3. DFD shows how the information moves through the system and how it is modified by a series of transformations. It is a graphical technique that depicts information flow and the transformations that are applied as data moves from input to output.
4. DFD is also known as bubble chart. A DFD may be used to represent a system at any level of abstraction. DFD may be partitioned into levels that represent increasing information flow and functional detail.

User:

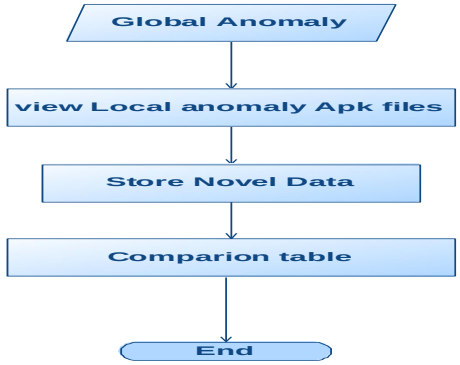
ADMIN



International Journal of Research
Available at https://edupediapublications.org/journals
p-ISSN: 2348-6848
e-ISSN: 2348-795X
Volume 03 Issue 13
September 2016



Global Anomaly:



UML DIAGRAMS:

UML stands for Unified Modeling Language. UML is a standardized general-purpose modeling language in the field of object-oriented software engineering. The standard is managed, and was created by, the Object Management Group.

The goal is for UML to become a common language for creating models of object oriented computer software. In its current form UML is comprised of two major components: a Meta-model and a notation. In the future, some form of method or process may also be added to; or associated with, UML.

The Unified Modeling Language is a standard language for specifying, Visualization, Constructing and documenting the artifacts of software system, as well as for business modeling and other non-software systems.

The UML represents a collection of best engineering practices that have proven successful in the modeling of large and complex systems.

The UML is a very important part of developing objects oriented software and the software development process. The UML uses mostly graphical notations to express the design of software projects.

GOALS:

The Primary goals in the design of the UML are as follows:

Provide users a ready-to-use, expressive visual modeling Language so that they can develop and exchange meaningful models.

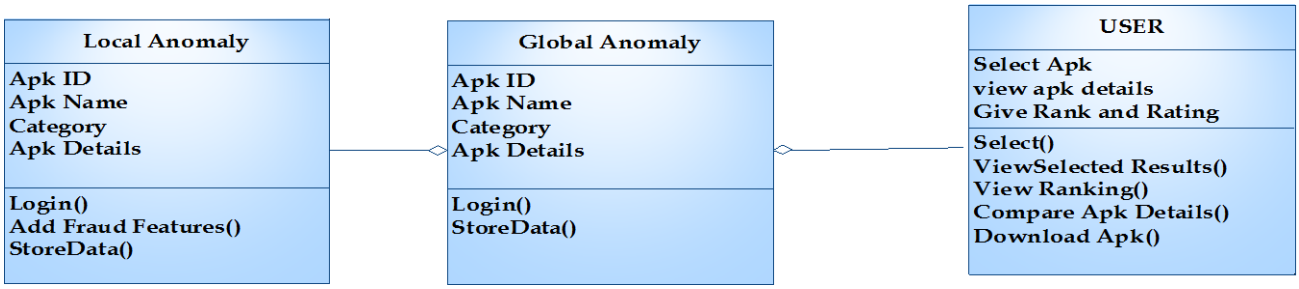
1. Provide extendibility and specialization mechanisms to extend the core concepts.
2. Be independent of particular programming languages and development process.
3. Provide a formal basis for understanding the modeling language.
4. Encourage the growth of OO tools market.
5. Support higher level development concepts such as collaborations, frameworks, patterns and components.
6. Integrate best practices.

USE CASE DIAGRAM:

A use case diagram in the Unified Modeling Language (UML) is a type of behavioral diagram defined by and created from a Use-case analysis. Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases. The main purpose of a use case diagram is to show what system functions are performed for which actor. Roles of the actors in the system can be depict

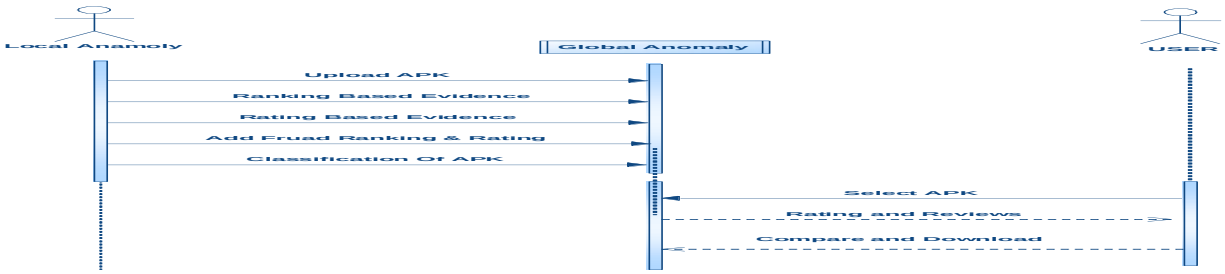
CLASS DIAGRAM:

In software engineering, a class diagram in the Unified Modeling Language (UML) is a type of static structure diagram that describes the structure of a system by showing the system's classes, their attributes, operations (or methods), and the relationships among the classes. It explains which class contains information.



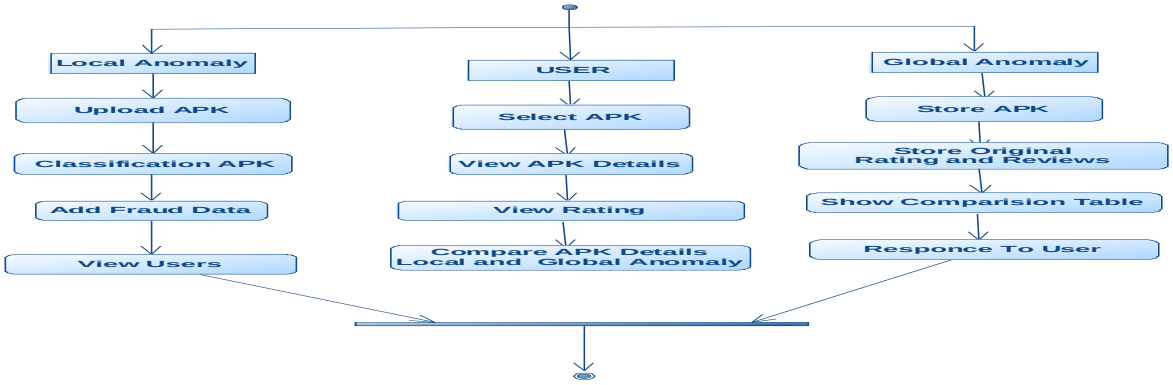
SEQUENCE DIAGRAM:

A sequence diagram in Unified Modeling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart. Sequence diagrams are sometimes called event diagrams, event scenarios, and timing diagrams.



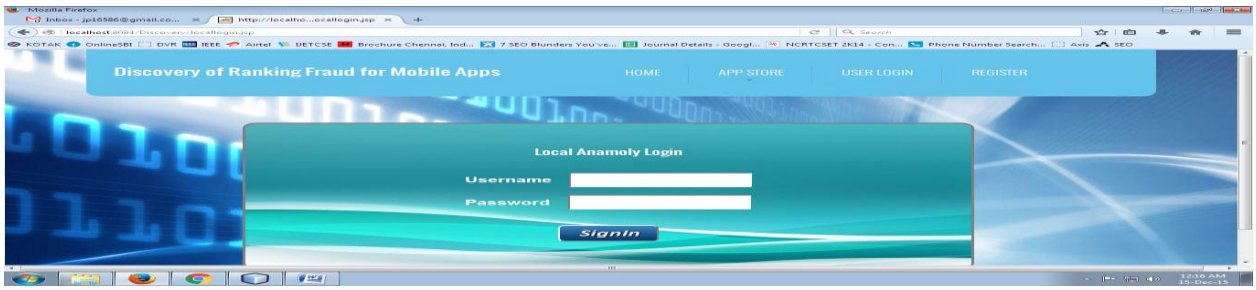
ACTIVITY DIAGRAM:

Activity diagrams are graphical representations of workflows of stepwise activities and actions with support for choice, iteration and concurrency. In the Unified Modeling Language, activity diagrams can be used to describe the business and operational step-by-step workflows of components in a system. An activity diagram shows the overall flow of control.



SCREEN SHOTS:

International Journal of Research
Available at https://edupediapublications.org/journals
p-ISSN: 2348-6848
e-ISSN: 2348-795X
Volume 03 Issue 13
September 2016



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.

REFERENCES:

[1] (2014). [Online]. Available: http://en.wikipedia.org/wiki/ cohen's_kappa

[2] (2014). [Online]. Available: http://en.wikipedia.org/wiki/ information_retrieval

[3] (2012). [Online]. Available: https://developer.apple.com/news/ index.php?id=02062012a

[4] (2012). [Online]. Available: http://venturebeat.com/2012/07/03/ apples-crackdown-on-app-ranking-manipulation/

[5] (2012). [Online]. Available: http://www.ibtimes.com/applethreatens-crackdown-biggest-app-store-ranking-fra ud-406764

[6] (2012). [Online]. Available: http://www.lextek.com/manuals/ onix/index.html

[7] (2012). [Online]. Available: http://www.ling.gu.se/lager/ mogul/porter-stemmer.

[8] L. Azzopardi, M. Girolami, and K. V. Risjbergen, "Investigating the relationship between language model perplexity and ir precision-recall measures," in Proc. 26th Int. Conf. Res. Develop. Inform. Retrieval, 2003, pp. 369–370.

[9] D. M. Blei, A. Y. Ng, and M. I. Jordan, "Latent Dirichlet allocation," J. Mach. Learn. Res., pp. 993–1022, 2003.

[10] Y. Ge, H. Xiong, C. Liu, and Z.-H. Zhou, "A taxi driving fraud detection system," in Proc. IEEE 11th Int. Conf. Data Mining, 2011, pp. 181–190.

[11] D. F. Gleich and L.-h. Lim, "Rank aggregation via nuclear norm minimization," in Proc. 17th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining, 2011, pp. 60–68.

[12] T. L. Griffiths and M. Steyvers, "Finding scientific topics," Proc. Nat. Acad. Sci. USA, vol. 101, pp. 5228–5235, 2004.