

Privacy and Security Behavior Prediction with Guarantee Solution for Mobile App Recommendation

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Abstract— In the past few years the usage of smart phone got increased and the plenty of mobile apps are introduced to solve various computational needs. Since many apps with duplication and malicious app product was in market the user get involved in using the un-safe apps with the knowledge that there are working with a proper app, so to overcome this disadvantage a recommendation scheme was introduced by the developer. Even though various existing methodologies provide a scheme to perform a recommendation in selecting the mobile apps it was not an effective one. So to overcome the drawback in the existing recommendation scheme, a proposed methodology was introduced in this paper that deals with popularity recognition, Further, it includes three types of recommendations, namely filtering session (Hybrid filtering), mining the context aware of user and location based recommendation. The main objective of the proposed work is about mining the personal context- aware of the user from the context log or the rich context device. Then app is recommended based on the user preference and location based. It also concerns about the security level of mobile app by a security algorithm named Automatic security detection. Finally, the recommendation of the apps was done based on frequent usage and location of user with privacy.

Keywords— *mobile app, recommendation, ranking, rating, review, location, mining, context-aware*

I. INTRODUCTION

Basically the mobile app is a computer program, it is deliberate to scurry on the smart phones, tablet or computer and supplementary mobile phones. The apps are typically pertinent through the application distribution platform, which begin appearing in 2008 and some of mobile operating system like Apple Appstore, Google play, Windows phone store and black Berry App World, which was commonly operated and managed by the proprietor . There is millions of mobile app available for the smart phones. A few of the apps are free of charge, at the same time as others have to be bought.

Usually the apps are downloaded from this platform to a target device, such as iPhone, blackberry, android phone or windows mobile, but sometimes they can be downloaded to a laptop or computer system. The shorter form of “application software “is the mobile app. The 20-30% percentage of app price goes to the distribution provider E.g. iTunes, and the remaining goes to the creator

of the app. The mobile apps were initially vacant for the universal production and information retrieval, including calendar, contact, email, stock market and about the weather information. The app availability based on the public demand, so the designer tools herd fast and rapid extension of mobile app into various other kind such as games in mobile, factory computerization, services based on GPS and based on location, banking, ticket purchasing... etc. There is a challenging issue in mobile app recommendation, because of sudden increase in quantity and the variety of mobile apps which in turn led to the conception of broad range of review and creation sources including blogs, magazines and online app services.

In existing the recommendation about the nearest park, restaurant, there is not availability of user frequent use[1]. There is a still exigent issue in taking out the personal context-aware of the user[8]. In fact, the contextual information and appropriate record usage canister be recorded into context rich device log or else context log which can be worn for mining personal context aware of the users. The user preference based on the personal context-aware recommendation system is able to furnish better user experience than traditional context-aware recommendation system[4]. The common context-aware recommendation include only the information of contextual nevertheless consider about the user’s preferences under the similar point of view.

The context log is enclosing all breed of information/behavior of the mobile user. On existing method deals with the popularity of App it is based on only ranking only the ranking is not adequate for recommending the app so proposed system include some other filtering techniques such as rating and review. There is a grave challenge in extort the personal context-aware preferences from the context log. The context log of everyone personage of user might not restrain adequate data for mining his/her context-preferences. To bursting pack this decisive emptiness, in this paper proposed system deals with the filtering method (Hybrid filtering) and extort the personal-context, aware of user from the user and also identify the security level of app like high level, medium level and low level. The security level is detected without human intervention.

The user preferences are predicted to recommend the app for the mobile user[6]. Generally the input gets from the user and the output is recommended based on their inclination, choice of the customer or user. In offline stage the context-aware is allowed for mining the user details depends on the assumptions like independent and dependent and use bi-pirate graph for matching the preferences.

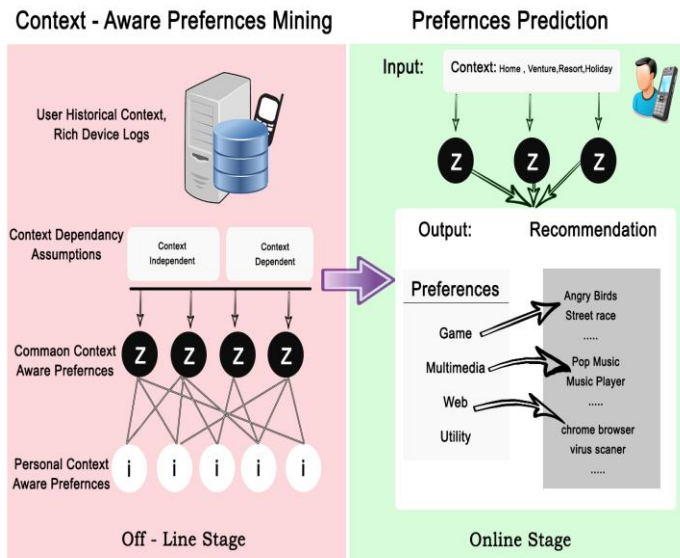


Fig.1. Framework for mining user preferences

Fig.1. Shows about the how the user preference is predicted from the context-aware. The context aware has four stages historical records, context dependency assumptions (is further divided into two categories independent and dependent), common context-aware preference and personal context aware preference. The common context-aware preference and personal context aware preference were matched by bi-pirate graph. In online stage the user discovered preference is recommended. Finally, the proposed loom using a real-world data set with personal context log composed commencing 500 mobile users. Entirely there are 10 million context reports. This data set contains a lot of context-rich information. The Matrix factorization techniques are used for mining context-aware preference and Regard as only which are significant to content usage for reducing the computation complication.

II. TYPES OF METHODOLOGY

In this session describe about how to identify, extort and unite fraud proof to detect the fake App and filtering approaches.

A. Hybrid Recommender System

The hybrid approach for recommendation, is the combination of collaborative and content-based filtering it will be might survive most valuable or effectual. Hybrid approaches can be implemented in numerous traditions: for

creating the content and the collaborative-based predictions one by one and afterward coalesce them; via accumulating transformation from content toward the collaborative-based approach (furthermore vice versa); or by unifying the approaches into one model. There are quite a lot of studies empirically compare and evaluate the presentation of the hybrid amid the wholesome collaborative and the content-based methods in addition to make obvious that the hybrid methods can offer more accurate recommendations rather than pure approaches. These methods preserve also be used to conquer various of the widespread evils in the recommender schemes for instance like cold start plus the sparsity problem

A good example of the hybrid recommendation system is Netflix. It is recommended by comparing the habit of similar users' activities such as watching and searching (e.g. Collaborative filtering) it also offers some movies that share characteristics film which is highly rated by the user (e.g. Content based filtering).

The hybridization is used seven types of techniques such as weighted, switching, mixed, feature combination, feature augmentations, cascade and meta level.

Weighted is about the scores of different recommendation and combine numerically.

Switching is used to select the system among recommendation components and applies selected ones.

Mixed is used to recommendation from multiple kind of recommenders are collectively obtainable.

Feature mixture is helpful for deriving the feature from different source are combined together and provide to a single recommendation algorithm.

Feature augmentation it provides one recommendation technique to work out for a aspect or collection of features then it will be the piece of the input to the subsequent method.

Tumble it is about the priority of the recommender with breaking the lower score priority.

Meta level is once the techniques are applied to recommendation techniques it give related sequenced model and it will be the input to next techniques.

a) Collaborative Filtering: collaborative scheme is depend on bring together data and also scrutinize a bulky quantity of source or data on users' mode of acting, otherwise fondness and envisage related to user desire, resemblance of other kind of users. The major advantage of using the collaborative sieve or filter loom so as to it sholud not count on machine analyzable content and therefore it is capable of accurately recommending complex items such as movies without requiring an understanding of the item itself. Lots of algorithms encompass for use in measuring user similarity in recommender systems, Collaborative Filtering are based on the assumption that people who agree with a past will agree in the later period also, and they will resembling the related kinds of items they like in the past.

When develop a model from user profile a distinct is often made between implicit and explicit data collection.

Examples of data collection explicit, contain the following:

- Request a user to pace a thing or item on a sliding scale.
- User is requested to search.
- Users are requested to give rank for collecting works of thing, or items from most desired to least desired.
- Two items are offered to a user and request them to select the best one among them.
- Users are requested to generate a record of thing, or what items they desire

Some of the examples of data collection of implicit as Follows:

- Listen or observe the thing or item which was viewed by the user in online.
- Predict the other times and views of users
- Collect and keep the proof or documentation about what items are purchased by the user in online.
- Collect the record and show the list about whatever the user viewed or watched on their system
- Predict the historical records of a user's social network and find the similar likes or desire and detest

Content-Based Filtering: Content-based filtering methods are based on a description of the item and the user's favorite summary. In a content-based recommender approach, the keywords are worn to explain about the thing or items; next the user profile is used to develop a record about which items are others like to use often. In other words, this algorithm is used to recommend items which are related to the user desire that in their earlier period (or is to groping in the current). With a scrupulous number of customer items are compared with earlier period item which was rated by users and finest corresponding or similar items are recommended

A key issue with content-based filtering is whether the system is able to learn user preferences from a user's actions regarding one content source and use them across other content types. When the system is limited to recommending content of the same type as the user is already using, the value from the recommendation system is significantly less than when other content types from other services can be recommended. For example, recommending news articles based on browsing of news is useful, but it's much more useful while listening music, playing videos, buying products, making discussions, etc. from this variety of services will be recommended whenever news browsing are available related to that.

The dissimilarity among the collaborative and content-based filter method canister be established by contrast of two well-liked or familiar musics like song recommender systems last. FM as well as Pandora radio

The Pandora make use of the details about the song or performer in order to initiate a "location" that plays songs with related material goods or details. The user's comment or opinion is used to filter the location consequences,

Reduce or minimize the importance about the items which are disliked by the user and give more priority to the item which was user liked to use often music. This is paradigm for content-based loom.

Last. Fm generates a "location" of recommended songs by scrutinizing what bands and tracks individually about what the user usually listen, then compare and evaluate which are not matched to the actual listening deeds of other users. Last. Fm will often play the track which was disappearing in the user's records. It also plays which was related curiosity to another user. In this approach it holds or grasps the deeds of the user, (The paradigm for collaborative filter method is mentioned above). For example, last. Fm the large amount of information is needed for a user record in order to compose perfect recommendations. The example of the cold start trouble is shown above and it is usual in collaborative filtering approach. While the Pandora require a very small amount of information or details to get started, it is more inadequate in capacity (for instance, it only gives recommendations which are related to the novel seed)

III. DISCOVER LEADING SESSIONS AND EXTRACTING EVIDENCES OF MOBILE APPS

A. Mining leading session

The App leader board plays the important role in promoting the app. If the particular App has a higher rank in the leader board, then it gives more turnovers to the developer. So usually some of the developers always try to do some disingenuous activity to boost their app as top rank in the rank chart. The leading events are discovered by the leading session with the help of confederacy flanking leading session[3]. The mining session has two steps respectively; initially we need to locate the leading events from the App's chronological records. Next is necessitating combining the flanking events for constructing the leading sessions.

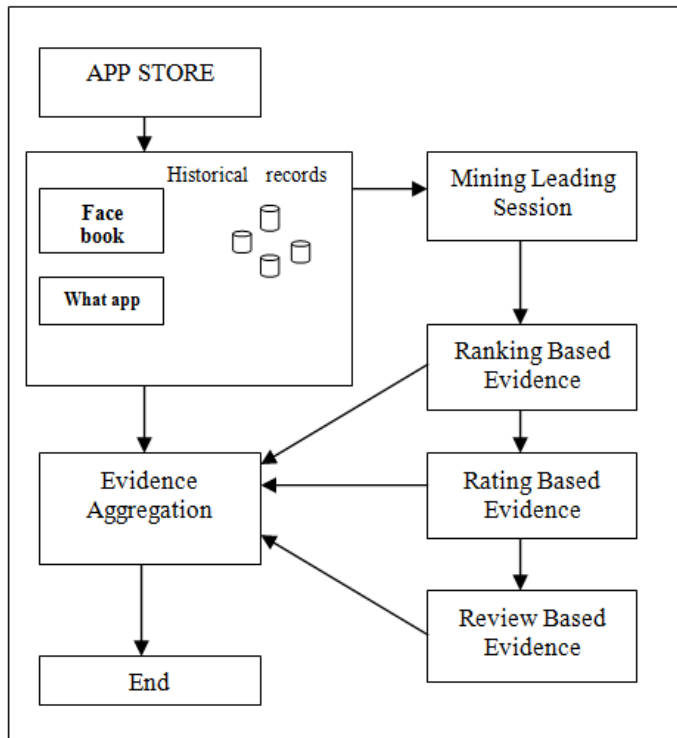


Fig.2. Framework for discovering fake rank

B. Ranking

Ranking is done by analyzing the chronological ranking records of Apps, it also examines the App's ranking deeds in leading events[10]. Supplementary it has three phases, namely rising phase, maintaining phase and recession phase. The rising phase is described about the top level on the leader board. The maintaining phase is regarding how long the app stay in the top level and recession phase is about the decrease or the end of the app or event. Moreover, after attaining and uphold the predictable or estimated rank at a vital period, then the manipulation was ended immediately this leads the malevolent app to decrease automatically. As a result the mistrustful app or event which has very small period of time in rising and recession phases. Consequently the fake app has only a limited time period in the top rank level or positions.

The Fig.2 show how the leading session is taking out the leading event taking from the historical records of mobile app. The leading event is mined by the mining leading session algorithm[7][2]. The threshold value is used to predict the top leading app or event. The threshold value contains the boundary value, condition of the event or session start and the session end.

The session start time is denoted as 't' and end time of the session is named as 'd'. The leading session completely depends on the threshold value.

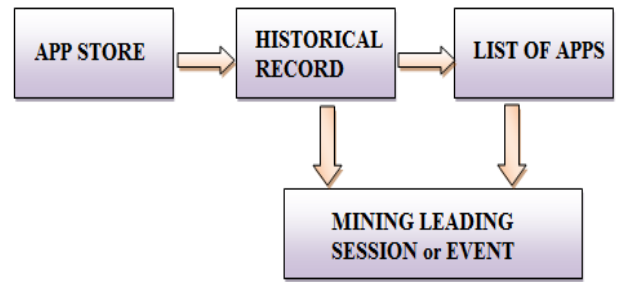


Fig.3. Framework for mining leading event or session

If the app once attains a top rank in the leader board, obviously it has a number of fans and it attracts very much and easier to download the app.

C. Rating

Ranking is not only enough to recommend the correct app so proposed system also considers the rating. The rating is an essential feature for the advertisement of app. The higher rating app pulls towards the user to download. But there is also some fraud action is committed.

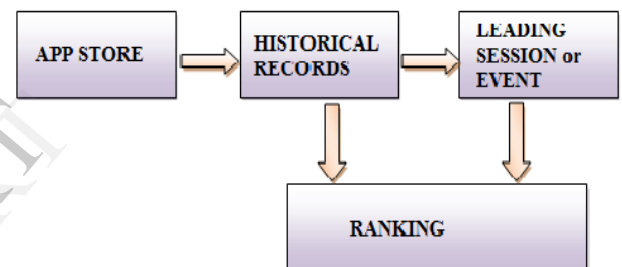


Fig. 4 Framework for ranking

Fig.4 demonstrates the ranking workflow process, the ranking mainly depends on the output of the mining leading session and it also collects data from the chronological records. For example, the allotment of the usual rating of a familiar app "We chat" and a mistrustful app identified by this approach correspondingly. The original app will have only an average rating compared to apprehensive app per day.

D. Review

Review allow user to write some text or comment about the app. It is completely about the user experiences. Distinctively prior to downloading or purchasing new mobile app. User over and over again initially read its chronological review to alleviate their conclusion, making, optimistic review in mobile app it magnetizes the more user to download. Generally, before downloading or purchasing a new mobile app, customers often initially read its historical records to easily make a decision and if the app holds many optimistic reviews might magnetize many customers to download.

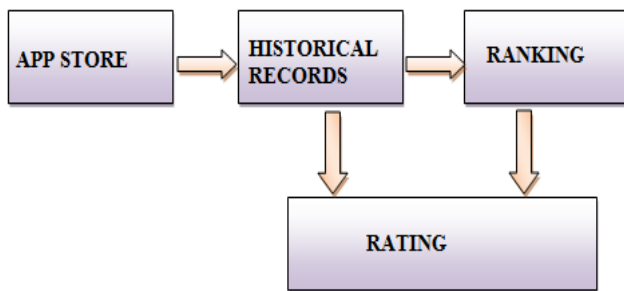


Fig.5. Framework for rating

In the above diagram demonstrate about the workflow of the rating. The rating is implemented to give a better recommendation because ranking doesn't only enough to for identify the fake app. The rating is also gathering data from the historical records. Hence, in the leading session pretenders habitually post forged reviews on particular app so as to increase the app to download, and it force the ranking position of the app on the leader board. Then the major problem is difficult to find the local variance of reviews in the leading session.

D. Fact Cumulative or Evidence Aggregation

Once extracting the types of methodology next challenging issue is how to merge this methodology for fraud detection. Instead of using the ranking, rating, review separately, we combine that all features for recommending the correct app. In fact, there are lots of cumulative methods in this paper, we proposed an unsupervised approach for combining the similarity of fraud apps[5]. To overcome the problem of local variance, it uses the following two principles

Principle 1: Pitiable evidence or fact will produce distinct scores from other applications, but efficient fact or evidence ought to have same evidence session.

Principle 2: The Pitiable evidence or fact will move to a further uniformly random ranking allocation or distribution, while the efficient evidence or fact ought to rank from same kind of conditional allocation.

IV. EXTRACTING PERSONAL CONTEXT-AWARE PREFERENCE FROM CONTEXT LOG.

A. Context Log

Context log consists of all kinds of information about the mobile user. These data are collected from the Google play or play store with the assist of some sensing apparatus of smart mobile. The smart mobile are typically equipped with a few contextual sensors, for instance GPS, 3D accelerometer and optical sensors. It facilitates them to confine the contextual information of mobile users and it provide a broad range of context service like context-aware tour guide, reminder based on location and context-aware recommendation. The context log is like a large database. The context – aware is the mobile device, it helps to optimize the mobile app recommendation. The context log is for the rich – contextual information about mobile user.

B. Mining Personal Context-aware

The mining personal context aware is based on preferences of mobile user. There is tranquil challenging in mining the personal context – aware preference[2]. The context log of each individual user doesn't have sufficient information (data). So we propose to uncover the common context – aware preferences from the context log of several users and signify their preferences[1]. To enlarge a personalized context – aware recommender system we reflect on both context – aware preferences and the current contexts of users. It gives the superior recommendation, then the traditional context – aware recommender system because it contains only contextual information but not about the user preferences.

Example 1: (Stirring Example)

The two users Alice and Bob resembling to play on a mobile phone while they are taking on the train. The information is gathered on the smart mobile by the help of a crash the sensor. The two users are taking on a train it is sensed by 3D accelerometer they from college to home, sensed by GPS or Cell ID it was Friday evening it is sensed by the system clock and the light was dark or low it is sensed by the optical sensor. By considering the personal context aware it gives better recommendation.

E.g.: Alice often plays shooting game and Bob often listens Yuvan music by using these detail the recommendation like new up-comes of the games to Alice and new Yuvan music to Bob.

V. CONCLUSION

The proposed system is about discovering fake rank for mobile app by using fraud sense techniques and also for mining the personal context-aware of the contextual information. Initially the proposed system describes about the hybrid recommender this approach combining the collaborative filtering and content based filtering for the effective result. The hybrid recommender systems use seven types of techniques for better recommendations. To recommend the location collaborative filtering approach is used. It uses k nearest algorithms to search the nearest location. Content based filtering is used to search the app which was in the user's frequently used list. Then it identifies the fake ranked app, generally the fake rank is happening with the mining leading session. Then ranking, rating and reviews evidences are used for detecting the fake rank. Additionally, it uses evidence aggregation or a fact cumulative approach for amalgamate all cumulative methods. The proposed system uses an unsupervised learning approach for combining all, it gives better result compared to supervised learning approach because supervised learning approaches utilize only trained or qualified set of data. Finally an app recommended based on the user preferences. The future works are about providing the security for mobile apps much efficient way.

REFERENCES

- [1] R.Agarwal and R. Sriganth Fast Algorithm for mining association rules.In VLDB'94 pages 487-499,1994.
- [2] R.Bader , E.Neufeld , W. Woerndl , and v. Prinz. Context-aware poi recommendations in an automative scenario using multi-criteria decision making methods.In CaRR'11 pages 23-30,2011.
- [3] D.M.Blei,A.Y.Ng and M.I.Jordan.Latent dirichlet allocation.In Journal of Machine Learning Research,pages 993-1022,2003.
- [4] N.Eagle, A.Clauset and J.A.Quinn. Location Symentaic inference and predction for anticipatory computing.In AAAI Spring Symposium or Technosocial Predictive Analytics,2009.
- [5] T.Bao , H.Cao, E.Chen, J.Tian and H.Xiong. An Unsupervised approach to modeling personalized contents of mobile users.In ICDM'10,pages 38-47,2010.
- [6] H.Zhu,H.Xiong,H.Cao and J. Tian. Exploiting enriched contextual information for mobile app classification.In proceeding of 21st ACM International Conference on Information and knowledge management,CIKM'12,pages 1617-1621,2012.
- [7] H.Zhu,H.Xiong,Y.Ge,and E.Chen. Ranking Fraud Detection for mobile apps:A holistic view.In Proceeding of the 22nd ACM international conference on information and knowledge managemebt,CIKM'13,2013.
- [8] K. Shi and K.Ali. Get jar mobile application recommendations with very sparse data sets.In Proceedings of the 18th ACM SIGKDD international conference on knowledge discovery and data mining, KDD'12,pages 204-212. New york,NY,USA,2012.ACM.
- [9] B.Yan and G.Chen.Appjoy:personalized mobile application discovery.In Proceedings of the 9th international conference on mobile systems, applications and services.MobiSys '11,pages 113-126, New York,NY,USA, 2011.ACM
- [10] H.Peng,C.Gates,B.Sarma,N.Li,Y.Qi,R.Potharaju,C.Nita-Rotaru and I.Molloy.Using probablistic generative models for ranking risks of android apps.In Proceedings of the 2012 ACM Conference on computer and Communication Security,CCS'12,pages 241-252,New york,NY,USA.2012.ACM.

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