# $\hfill \ensuremath{\mathbb{C}}$ April 2016 | IJIRT | Volume 2 Issue 11 | ISSN: 2349-6002 APP ZOO

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*Abstract*— The technology is used to pinpoint person's location and provide location-specific applications on their mobile devices. Location of person who uses the application is trace with the help of GPS System. After tracking the location, the applications that suggested to him are according to his interest. The users who have used the application few times (already registered) are able to see the recent history. It provides what is buzzing around you i.e. news/views/events. Here we are using a client-Server architecture where the previously visited or accessed data is stored. So according to users profile details applications are shown to the users. This application includes a variety of contexts, such as entertainment, work, and personalized weather services and even location-based games.

Index Terms- GPS, Location based-games, recommendations, classification

#### I. INTRODUCTION

Recently, smart phones are not only limited for calling or texting purpose. They moved one step ahead and it becomes pervasive device. In this era, mobile provides different facilities such as, emailing, camera for selfie, social network access facility and also video calling. Many tools are available to design mobile apps and it becomes possible to everyone having minimum knowledge.

Multiple apps have similar functionality that is developed by different vendors. Therefore, it is required to have classification of mobile apps. Our proposed system helps to search required app easily and also app can be search by preferences of user. Our system provides intellectual services such as, app recommendation, user segmentation, target advertising etc. Therefore, Our system known as mobile app classification plays very important role for appropriate use of mobile apps. It is quite difficult to classify mobile apps as only limited contextual information is available. For classification of apps we extract detail description about app. Our main contribution in this system is to provide an effective classification of the mobile apps by using the enriched information about the apps. Furthermore, to achieve this goal we are extracting not only web knowledge but we focusing on real contextual features of app along with their names. It will automatically improve contextual information as well as make easier to app classification task. Google or from any app store

is for extraction of web knowledge of particular app. In our system, we are creating an application that provides an effective classification with more refined categories of application of the mobile apps.

#### **II. RELATED WORK**

This work proposes a location-based mobile advertisement publishing system, a framework for vendor editing, and location-based service. The system is able to provide vendors not only the ability to edit advertisements, but also the means to publish advertisements to consumers [1].

In order to capitalize on the large number of potential users, quality community detection and profiling approaches are needed. In the meantime, the diversity of people's interests and behaviors when using LBSNs suggests that their community structures overlap. In this section, based on the user check-in traces at venues and user/venue attributes, we come out with a novel multimode multi-attribute edge-centric co clustering framework to discover the overlapping and hierarchical communities of LBSNs users. By employing both intermode and intramode features, the proposed framework is not only able to group like-minded users from different social perspectives but also discover communities with explicit profiles indicating the interests of community members [2].

Large numbers of mobile apps with similar functionality are coming into the market due to the increasing use of mobile devices. Classifying these apps is useful to understand the user preferences which can motivate the intelligent personalized services and also while selecting the application. But turns out be a nontrivial task as limited information about the apps is directly available. In this section we have presented a method to classify the mobile apps using the information collected from the various sources like information from apps name, search engine, contextual usage history collected from the user's usage record and also the permissions of the app. This will provide us a secure and effective classification of the apps as most of these apps come from an unknown vendor and so there is higher possibility of them being malicious[3].

One of Android's main defense mechanisms against malicious apps is a risk communication mechanism which, before a user installs an app, warns the user about the permissions the app requires, trusting that the user will make the right decision.

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This approach has been shown to be ineffective as it presents the risk information of each app in a "stand-alone" fashion and in a way that requires too much technical knowledge and time to distill useful information. We discuss the desired properties of risk signals and relative risk scores for Android apps in order to generate another metric that users can utilize when choosing apps [4].

This paper introduces a hidden topic-based framework for processing short and sparse documents (e.g., search result snippets, product descriptions, book/movie summaries, and advertising messages) on the Web. The framework focuses on solving two main challenges posed by these kinds of documents: 1) data sparseness and 2) synonyms/homonyms. The former leads to the lack of shared words and contexts among documents while the latter are big linguistic obstacles in natural language processing (NLP) and information retrieval (IR). The underlying idea of the framework is that common hidden topics discovered from large external data sets (universal data sets), when included, can make short documents less sparse and more topic-oriented[5].

Measures the similarity between sparse text. Measuring similarities author's usage kernel functions. They also provide theoretical analysis for this kernel functions[6].

A methodology for building a practical robust query classification system that can identify thousands of query classes with reasonable accuracy, While dealing in real time with the query volume of a commercial web search engine. It is higher level task beneficial for searching over web and matching patterns. For matching similarity they assume plurality of highest level search. This system achieves higher accuracy[7].

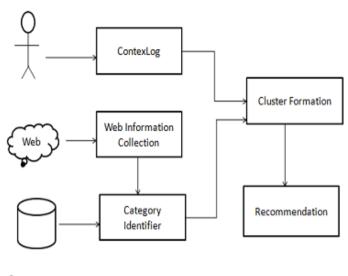
The progressing ability to sense user contexts of smart mobile devices makes it possible to discover mobile users with similar habits by mining their habits from their mobile devices. However some researchers have proposed effective methods for mining user habits such as behavior pattern mining, how to leverage the mined results for discovering similar users remains less explored. [8].

Today's smartphone operating systems frequently fail to provide users with adequate control over and visibility into how third-party applications use their private data. We address these shortcomings with Taint Droid, an efficient, systemwide dynamic taint tracking and analysis system capable of simultaneously tracking multiple sources of sensitive data[9].

Android provides third-party applications with an extensive API that includes access to phone hardware, settings, and user data. Access to privacy- and security-relevant parts of the API is controlled with an install-time application permission system. We study Android applications to determine whether Android developers follow least privilege with their permission requests [10].

Based on our findings, we present recommendations and opportunities for services that will help users safely and confidently use mobile applications and platforms [11].

## **III.PROPOSED SYSTEM**





# Figure 1: System Architecture

In previous system there was no personal recommendations and category classification of Application, for this purpose we are developing an app called AppZoo.

In App Zoo system there are two application interacting with each other to get proper App suggestion along with its risk level calculation.

First application is running on server that responds to the user queries and analyze the Apps web based features and also it calculates the contextual features of App stored at users end i.e personnel logs.

Second application is stored at users android mobile which is used to generate logs regarding particular App and send it to the server for analysis purpose. The user will get the effective classification of the apps along with their risk score. All these Apps are work integrally.

#### Contex Log:-

User will upload the app access logs to the server. The access log contains app name, usage, time, date and usage hours. Along with user profile user pro- file contains Gender, Education, age. Save the system collect the information and view the information in database.

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# Web Information:-

With respect to each app information of application is collected from web sources Google search snippet provides most relevant feature set. The top most K mapped snippets are retrieved from Google search. The information present in snippet is preprocessed and application category is identified with respect to predefined app category specification for identification of category, KL diversion methods are used.

### **Cluster Formation:-**

Based on the contex logs and Web based feature set data is classified.By mapping all the features of app category and user contex logs app can be classified with different categories such as, Most used app with respect to age group, Profile, Interest etc.

### **Category Identifier:-**

Access the Web Information and identifies the category. Stores the result in its own database. Further the data is processed for cluster formation.

#### **Recommendation:-**

User personal profile and its usage logs are uploaded to the server. By analyzing the contex log system identifies the user preferences and recommendation are generated as per user profile.

#### **User Working:-**

User get APK of App used to send logs.User install App.User register on server using our app and update profile. User access apps on his/her mobile.User app register access information.Upload Data to server. Search for application. Get recommendation.

#### **IV.ALGORITHMS**

# Algorithm 1:M<sup>2</sup> Clustering Algorithm: Input:

- E, an edge list  $\{ei | 1 \le i \le n\}$
- k, the number of communities
- Mu, the user-user similarity matrix
- Mv, the app-app similarity matrix

#### **Output:**

C, a set of detected communities

# Algorithm:

*1.k* edges are randomly selected { ej  $|1 \le j \le k$  } 2.for each *ej* do 3:  $ECj \leftarrow \{ej\}$ 4:  $EA, Cj \leftarrow ECj$ 5:  $ER, Cj \leftarrow \emptyset$ 6:  $sim(EP, Cj, E) \leftarrow zeros(|E|)$ 

- 7: end for
- 8: {maxsim $i | 1 \le i \le n$ }  $\leftarrow 0$
- 9: repeat
- 10: Objpre ←
- 11: reset { maxsimi }
- 12: for each Cj do
- 13: **for** each *ei* in *E* **do**
- 14: calculate sim(EA, Cj, ei)
- 15: calculate sim(ER, Cj, ei)
- 16:  $sim(ECj, ei) \leftarrow sim(EP, Cj, ei) + sim(EA, Cj, ei)$  -
- sim(ER, Cj, ei)
- 17: **if** sim(*ECj*, *ei*) > maxsim*i* **then**
- 18: maxsim $i \leftarrow sim(ECj, ei)$
- 19: assign *ei* to *Cj*
- 20: end if
- 21: end for
- 22: end for 23: update the centroids
- 24: Objcur ←

25: Delta ← abs(Objcur - Objpre)

26: until Delta < Threshold

# Algorithm 2: HM<sup>2</sup> Algorithm : Input:

- *E*, an edge list  $\{ei | 1 \le i \le n\}$
- *K*, a large number which is \_ *k*
- *Mu*, the user–user similarity matrix
- *Mv*, the app-app similarity matrix

#### **Output:**

• D, an edge dendrogram

# Algorithm :

- 1: invoke Algorithm to generate K edge groups {Gj}
- 2: calculate pairwise similarity W<sub>ab</sub> for connected edge groups *Ga* and *Gb*
- 3: repeat
- 4: find the largest  $w_{ab}$
- 5: merge Ga and Gb, update related weights
- 6: until |*G*| <= 1

# V. CONCLUSION

Effective classification of the mobile apps is important as everyday there are number of similar kind of apps coming in the market. Several classification techniques are available for classifying the short and sparse data, which can be adapted for classifying the mobile apps. But the result obtained from these techniques does not give us the effective classification of the apps, as they take into consideration only single factor for classification i.e. web knowledge or contextual information. So we have proposed an approach to effectively classify the

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mobile apps in which we will extract the information from multiple sources in order to improve classification so as to provide more effective result. Our system improves the security concerns of the malicious apps in easy to understand manner. As a part of contribution this will not only help the user to select the proper app according to his requirements but also as per his profile maintained at the system's end.

# REFERENCES

1. Chyi-Ren Dow, Yu-Hong Lee, Jeremy Liao, Hao-Wei Yang and Wei –Luen "A Loaction based Mobile Advertisement PublishingSystem for Vendor".

2. ZhuWang,Daqing Zhang,Xingshe Zhou, Dingqi Yang, Zhiyonng Yu and Zhiwen Yu "Discovering and Profiling Overlapping Communities in Location-Based Social Networks".

3. Hengshu Zhu, Enhong Chen, HuiXiong, Huanhuan Cao, and JileiTian,"Mobile App Classification with Enriched Contextual Information ",IEEE Transactions on mobile computing (Volume:13, Issue:07),7 July 2014.

4. Christopher S. Gates, Ninghui Li,Peng,BhaskarSharma,Yuan Qi, Rahul Potharaju,Cristina Nita-Rotaru and Ian Molloy, \Generating Summary Risk Scores For Mobile Applications",IEEE Transactions on dependable and secure computing (Volume :11, Issue: 03),May-June 2014

5. X.-H. Phan et al., A hidden topic-based framework toward building applications with short web documents, IEEE Trans. Knowl.Data Eng., vol. 23, no. 7, pp. 961976, Jul. 2010

6. M. Sahami and T. D. Heilman, A web-based kernel function for measuring the similarity of short text snippets, in Proc. WWW, Edinburgh, U.K., 2006, pp. 377386

7. A. Z. Broder et al., Robust classification of rare queries using web knowledge, in Proc. SIGIR, Amsterdam, Netherlands, 2007, pp. 231238.

8. H. Ma, H. Cao, Q. Yang, E. Chen, and J. Tian, A habit mining approach for discovering similar mobile users, in Proc. WWW, Lyon, France, 2012, pp. 231240.

9. W. Enck, P. Gilbert, B. Chun, L.P. Cox, J. Jung, P. McDaniel, and A.N Sheth, TaintDroid: An Information-Flow Tracking System for Realtime Privacy Monitoring on

Smartphones, Proc. Ninth USENIX Conf. Operating Systems Design and Implementation, article 1-6,2010

10. A.P. Felt, E. Chin, S. Hanna, D. Song, and D. Wagner, Android Permissions Demystied, Proc. 18th ACM Conf. Computer and Comm.Security, pp. 627-638, 2011.

11. E. Chin, A.P. Felt, V. Sekar, and D. Wagner, "Measuring User Confidence in Smartphone Security and Privacy, Proc. Eighth Symp. Usable Privacy and Security, (SOUPS 12), article 1, 2012.