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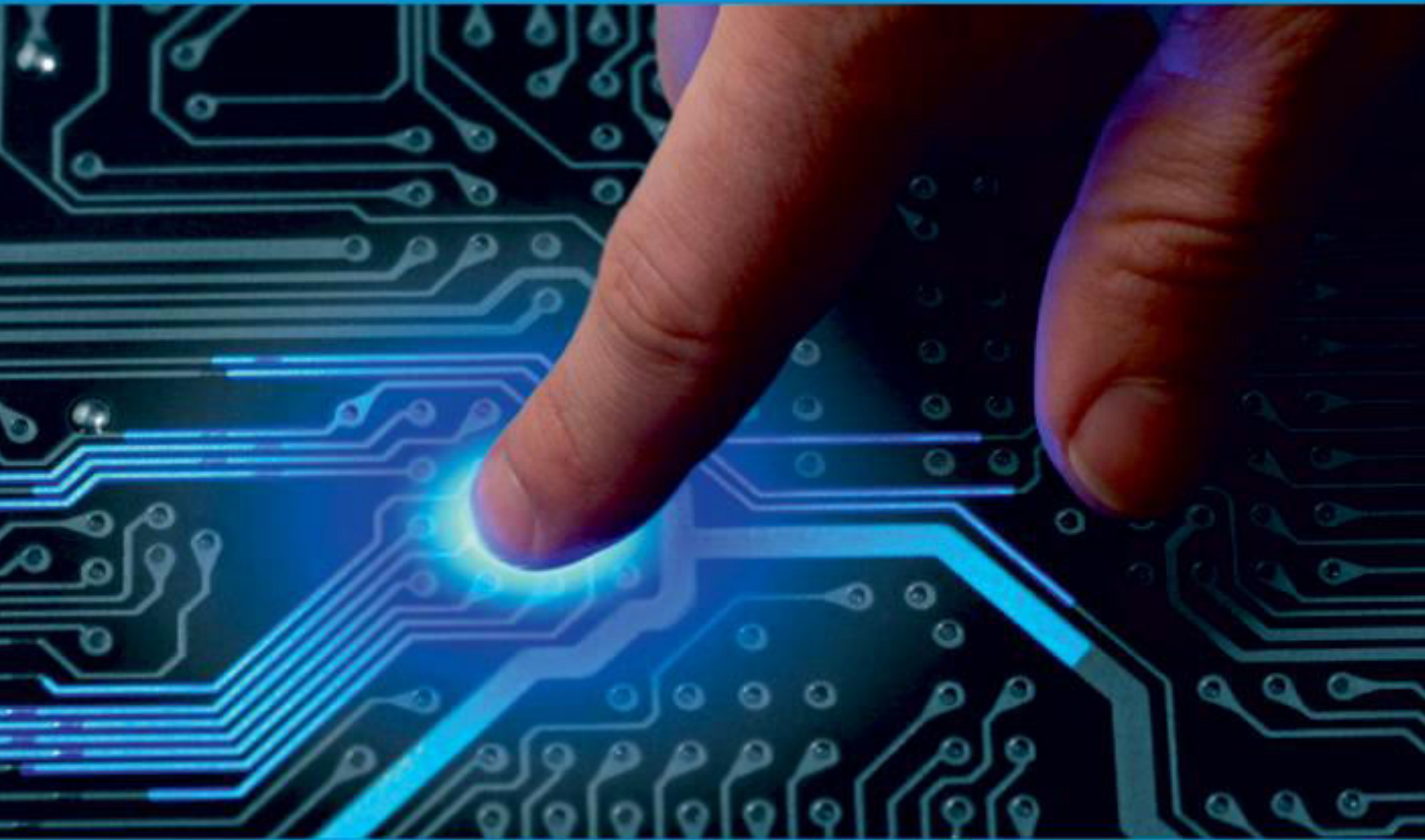

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# App Recommendation System Using Social Interest

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**ABSTRACT:** Human life has drastically changed due to the increase in the popularity and growth of the mobile devices and mobileapps. If the number of smartphone apps continues to rise, discovering apps for people will only become more difficult. We suggest anapp-based recommender that integrates the textual data of social media i.e. Sent posts as well as user interest. We apply topic modellingon social media data to derive topics, and the features of the apps. In addition, user interests are then taken into consideration when constructing the profile. All of the app's subject distributions, as well as the app preferences, are analysed to create customised lists ofsuggested content for each user. In order to find out whether the environment is different from the design, we use real-world data sets.This experiment has found that social media data such as user generated posts is successful for characterising users' interests, and the proposed application relies on that knowledge.

**KEYWORDS**: Energy efficient algorithm; Manets; total transmission energy; maximum number of hops; network lifetime

## I. INTRODUCTION

In this paper, we capitalize on user reviews to understand the functionalities of apps from the users' perspective and leverage user reviews to develop an app recommender system. The topics hidden in the review texts can be a type of representation of the app features. We collect user reviews from app stores to perform topic modelling and represent each app as the probabilities of topic distributions. Then, user preference is inferred from the topic distribution of the user's consumed apps to construct the user profile.

It has brought significant benefit to the human race as a result of the increasing proliferation and innovation of smartphones and mobile apps. Many applications have been created to help different users with everyday functions, such as work, entertainment, and exercise. There are countless applications available on the iTunes store and Google Play store. People are having a hard time finding suitable apps because of the large number of mobile applications; very few have a real impact on them. Solving the problem of helping end users achieve their expectations therefore becomes crucial.

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Recommender systems have become a mainstay of the Internet, helping consumers wade through an ocean of data to choose what they would like to buy. There are a number of common recommendation and app strategies that can be used in app stores, such as collaborative filtering (CF) and content-based filtering, to improve relevance for users. This model assumes that customers who've provided similar ratings on different products are likely to choose similar items. There is a notion that people's desires are encapsulated in the things they browse, and those items that are more of the preferred items are subsequently displayed.

We gain insight into app functionalities from the user's viewpoint by capitalising on users and design a user app recommender framework from that point of view. The topics in the application analysis texts are an example of application functionality. To reflect each app as the probabilities of topic distributions, we collect user feedback from app stores. Based on what the user uses, their profile is constructed from such applications. These topics that the user likes or dislikes can be used to help find more useful features for the user. Recommendation ratings are used to generate both the topics for users, and app choices that are highly important to them.

## II. REVIEW OF LITERATURE

In this paper, author propose a method based on machine learning to predict users' app usage behavior using several features of human mobility extracted from geo-spatial data in mobile Internet traces. The core idea of our method is selecting a set of mobility attributes (e.g. location, travel pattern, and mobility indicators) that have large impact on app usage behavior and inputting them into a classification model.

In this work, author challenge these elementary characterizations of smartphone users and show evidence of the existence of a much more diverse set of users. Author analyzed one month of application usage from 106,762 android users and discovered 382 distinct types of users based on their application usage behaviors, using our own two-step clustering and feature ranking selection approach.

In this paper, authors first highlight the importance of different types of ties in social relations originated from social sciences, and then propose a novel social recommendation method based on a new Probabilistic Matrix Factorization model that incorporates the distinction of strong and weak ties for improving recommendation performance.

Author proposes to use the linked users across social networking sites and ecommerce websites (users who have social networking accounts and have made purchases on e-commerce websites) as a bridge to map users' social networking features to another feature representation for product recommendation. In specific, we propose learning both users' and products' feature representations from data collected from e-commerce websites using recurrent neural networks.

In this paper author present the first population-level, city-scale analysis of application usage on smartphones. Using deep packet inspection at the network operator level, we obtained a geo-tagged dataset with more than 6 million unique devices that launched more than 10,000 unique applications across the city of Shanghai over one week. We develop a technique that leverages transfer learning to predict which applications are most popular and estimate the whole usage distribution based on the Point of Interest (POI) information of that particular location.

In this paper, author demonstrate that it is possible to make personalized app usage estimation by learning user's app preference from the social media, i.e., public accessible tweets, which can also reflect user's interest and make up for the sparsity of app usage data. By proposing a novel generative model named IMCF+ to transfer user interest from rich tweet information to sparse app usage, authors achieve personalized app recommendations via learning the interest's correlation between apps and tweets.

In this paper, author propose DPLink, an end-to-end deep learning based framework, to complete the user identity linkage task for heterogeneous mobility data collected from different services with different properties.

We're using Apkpure.com, which is a well-known Android software store, as well as Web Crawler, which collects information about a website and validates linkages. Following that, apps are grouped or clustered based on Popularity, Permission, and Security factors using the Clustering Algorithm.The goal of this work is to provide a basic recommendation system that does not sacrifice rating, size, or permission elements.

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## III. SYSTEM DESIGN

### A) System Architecture

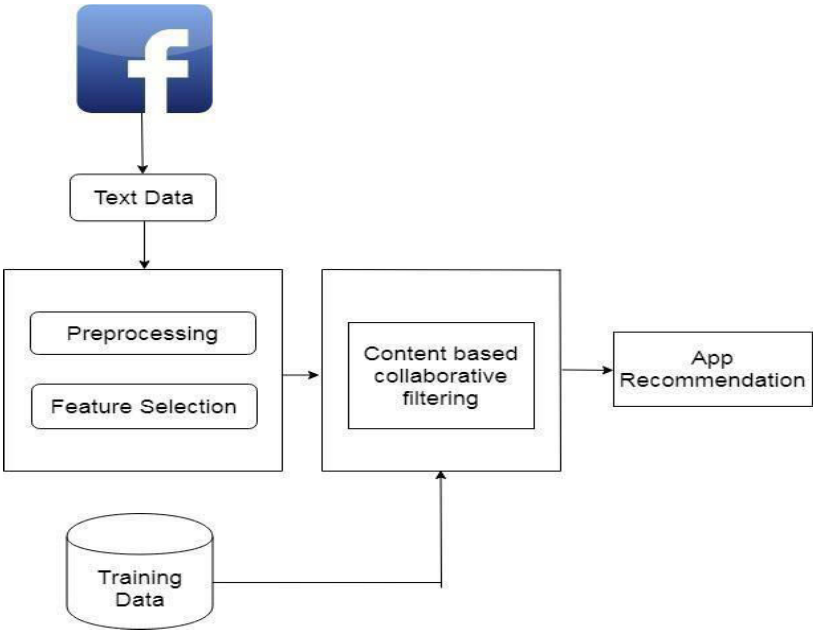


Fig 1. Proposed System Architecture

**Data Flow Diagrams:**

**1) Level 0 data flow diagram:**

a. The DFD is also called as bubble chart. It is a simple graphical formalism that canbe 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.

b. The data flow diagram (DFD) is one of the most important modeling tools. It isused 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 ows in the system.

c. Figure 4.1 shows level 0 DFD which shows how the information moves throughthe system and how itis modified by a series of transformations. It is a graphical technique that depicts information ow and the transformations that are applied as data moves from input to output.

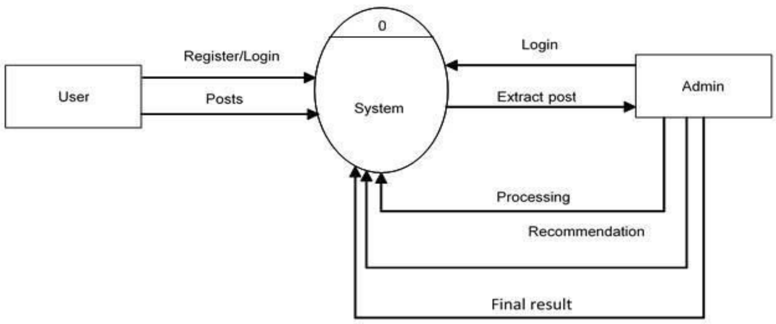


Fig 2. DFD Level 0

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**2) Level 1 Data Flow Diagram:**

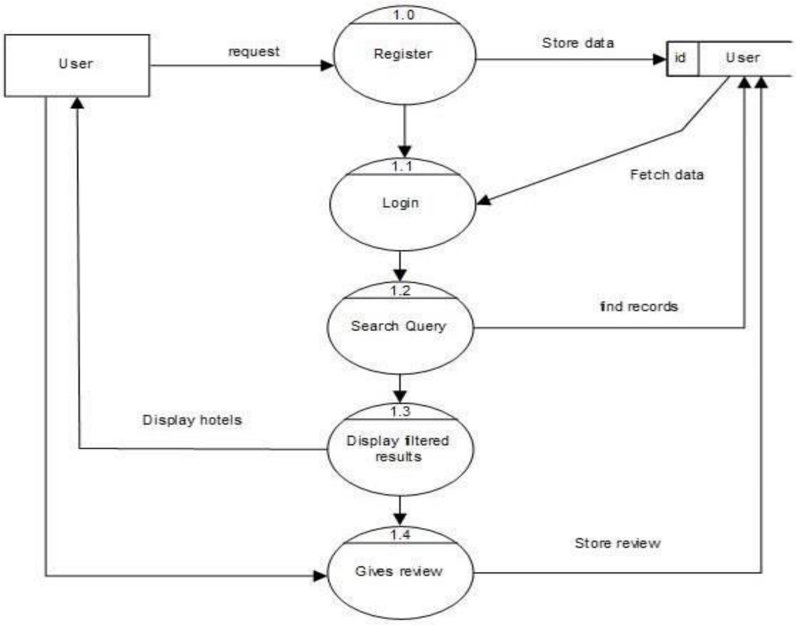


Fig 3. DFD Level 1

**B) Algorithm:**

Step 1: Facebook Data collection using Facebook streaming API and Facebook comments collection using online tools like extract comments.com, etc.

Step 2: Data pre-processing like removal of duplicate posts, stop words.Step 3: Data normalization using porter

stemming algorithm.

Step 4: Data loading on Dataset.

Step 5: Design and Implementation of program for per day frequency of posts.Step 6: Design and Implementation of

program for feature selection.

Step 7: Facebook post Classification. Step 8: Mobile app recommendations.

**1) Dataset**

Facebook Dataset

Facebook has billions of users and it is one of the most used website/app used in the world. A lot of data are generated on Facebook daily. Here, we are going to look at an anonymized dataset named pseudo-facebook.csv. We are interested in looking at the various trends and distribution of the parameters in our data.

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**2) Mathematical Model:**

Create the user's profile in three separate but linked stadiums: post keywords, post named individuals and post distributions on topics. The user should convey any profile as

_ _ _ _ V u =< F u; G u; E u

This corresponds to the three-stage model of posts. However, there are some differences between this and the profile of posts, where

_ _ _ _ _ _ F u = f 1; w 1; t 1; f 2; w 2; t 2; : : : :; F u

Represents keywords that the user has accessed from historical posts, and any entry consists of a representative phrase, weight, and the last time that the user has accessed it;

_ _ _ _ _ _ E u = e 1; w 1; t 1; e 2; w 2; t 2; : : : :; E u

Represents the named entities that have been compiled from the user's historical posts and each entry consists of an approved authorization object, the weight and the last time the user has viewed them;; and

_ _ _ _ _ _G u = g 1; w 1; t 1; g 2; w 2; t 2; : : : :; G u

This reflects the distribution of subjects gathered from the users' historical entries, each entry consists of a representative theme id, a corresponding weight and the last time it was viewed by users.

## IV. CONCLUSION

In this paper, we leverage the information of user social media to design a personalized app recommender system. The topic modeling approach is applied to extract topics from the huge amount of textual data in user social data to model the features of apps, and the user's installed apps are capitalized to build the user profile to model user preferences. Both the user preferences and app features are taken into account to estimate the personalized app recommendation scores. Realworld data are utilized to perform experiments, and the experimental results show that the user reviews are effective for personalized app recommendations.

## V. RESULT

The Experiments are done by personal computer with configuration: Intel (R) Core (TM) i3-2120 CPU @ 3.30GHz, 4GB memory, Windows 7, MySQL 5.1 backend database and JDK 1.8. The application uses web application tool for design code in Eclipse and execute on Tomcat server.
Positive (P) : Observation is positive. Negative (N) : Observation is not positive.
True Positive (TP) : Observation is positive, and is predicted to be positive.False Negative (FN) : Observation is positive, but is predicted negative.

True Negative (TN) : Observation is negative, and is predicted to be negative.False Positive (FP) : Observation is negative, but is predicted positive.
Accuracy = TP + TN / (TP + FP + TN + FN)
Precision = TP / (TP + FP)Recall = TP / (TP + FN)

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F1-Measure = 2 * Precision * Recall / (Precision + Recall).

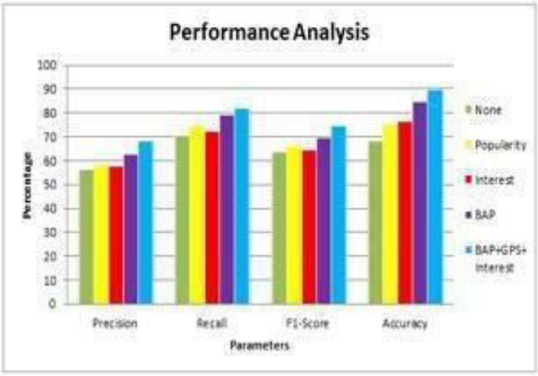


Fig. 3. Accuracy Graph

| | Existing System | Proposed System |
|---|---|---|
| Accuracy | 79.32 | 89.77 |

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