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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 mobile apps. If the number of smartphone apps continues to rise, discovering apps for people will only become more difficult. We suggest an app-based recommender that integrates the textual data of social media i.e. Sent posts as well as user interest. We apply topic modelling on 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 of suggested 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:** App recommendation, social media, transfer learning, collaborative filtering.

## I. INTRODUCTION

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.

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.

### A. Objectives

- To implement app recommendation system based on user social media data.
- Try to improve recommendation accuracy using content based collaborative filtering.
- Evaluate the performance of system based on real world app usage and facebook post datasets over a large population with a variety of scenarios and parameters.



## II. REVIEW OF LITERATURE

In this paper[1], the researcher shows that it is possible to make up for the paucity of usage data with learning about the user's app and his/her own interests by using public tweets. To connect people's immediate interests with app use, we create a new generative model called IMCF to predict each user's interest in an app. This paper[2] proposes a deep learning connection end-to-end architecture, called DPLink, to help with heterogeneous mobility data obtained from different services. The first population-wide study of smartphone application is described in this paper[3]. In analysing a dataset from the city of Shanghai, we compiled over 6 million unique devices that produced more than 10,000 unique applications over the course of a week that were tagged with GPS coordinates. The framework uses transfer learning to predict which apps will be popular, and also uses POI data to predict the entire application distribution based on location. It has been suggested that the use of cross-linked social networking sites and e-commerce accounts may aid in mapping people's social features into another product feature for recommendation. and we make the case for recurrent neural networks for deducing both consumer and product representations from online data that is collected. A graph embedding scheme, called GE, is proposed in this paper[4]. Conceptually, this integrates the sequential, regional, temporal, and semiotic impacts, but defines them all in a single lower-dimensional coordinate system. In order to capture real-time interests, authors create a novel time-decay approach that uses POIs that are embedded in the latent space to learn and return the user's current desires in real time. A new approach based on a probabilistic factorization model for better analysing social relationships is proposed in this paper[5]. In this, the new study, the author sets out to prove that people who use smartphones do not all belong to the same demographic. We studied the app use patterns of 106,762 Android users and uncovered 2 months of data and discovered 38 different user personas based on their app features. This paper [6] differentiates users according to the quantity of applications they have used, which allows users to be distinguished by their software signature. to better understand the app use in use by 46726 Mental participants. Through the use of machine learning, an author proposes[8] a method for predicting human mobility through various data, which is created from online sources, on his website's users' habits. The principle of our approach revolves around selecting a collection of behavioural features (e.g. location, travel habits, and mobility attributes) and making them part of a classification scheme. The key concept of this[9] approach is to pick a variety of mobility attributes (e.g. location, travel pattern and mobility indicators) which impact and integrate them into a classification model for app use. This approach is evaluated using our self-developed high-speed traffic monitoring system for real-world network traffic (TMS). this method of prediction reaches 90.3% precision in our experiment, which verifies the clear association between human mobility and application behaviour. One of the most[10] important issues of such processes is cold starting, i.e. when no previous experience is present and a new item is inserted in the system, so there cannot be any successful suggestions. In reality, the item cold starts are a very popular issue: hundreds of new pieces are released regularly on modern web platforms. In order to solve this issue, we propose to learn Local Collective Embedding's: a factorization matrix that takes advantage of property and previous user expectations when applying the diverse structure of group embedding. We have an educational algorithm built on several, easy-to-implement update laws.

## III. PROPOSED METHODOLOGY

The popularity and advancement of smartphones and mobile apps have brought considerable convenience to human life. A substantial number of mobile apps have been developed to assist users in various types of tasks, such as production, entertainment, and exercise. Millions of apps are available for downloading from the Apple App Store and Google Play Store. With such a tremendous and still rapidly growing number of mobile apps, users face difficulty in finding appropriate apps, and only a few apps have the chance to be exposed to users. Hence, helping users to find apps that meet their demands is a critical issue.

## A. Architecture

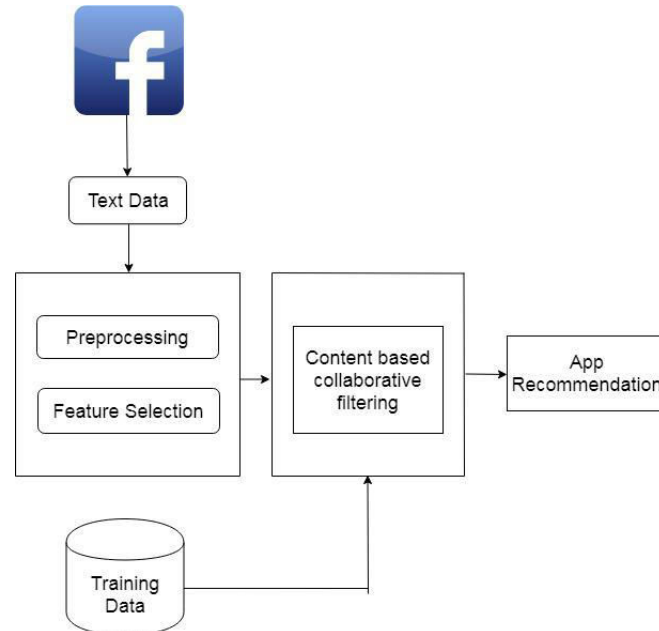


Fig. 1. Proposed System Architecture

## 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.

## C. 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.





#### D. 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

$$V_u = \langle F_u; G_u; E_u \rangle$$

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

$$F_u = \langle f_1; w_1; t_1; f_2; w_2; t_2; \dots; f_n \rangle$$

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;

$$E_u = \langle e_1; w_1; t_1; e_2; w_2; t_2; \dots; e_n \rangle$$

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

$$G_u = \langle g_1; w_1; t_1; g_2; w_2; t_2; \dots; g_n \rangle$$

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. RESULTS AND DISCUSSION

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.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{F1-Measure} = 2 * \text{Precision} * \text{Recall} / (\text{Precision} + \text{Recall}).$$

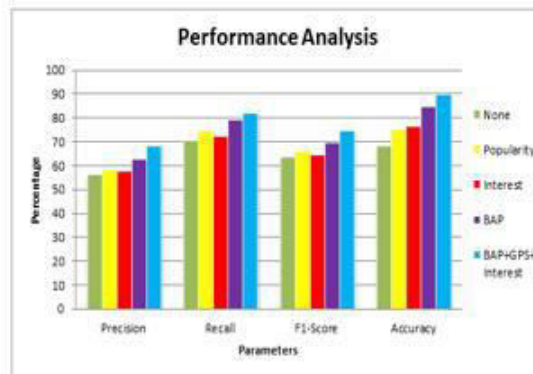


Fig. 3. Accuracy Graph

	Existing System	Proposed System
Accuracy	79.32	89.77

### V. CONCLUSION

We incorporate the knowledge that users have about their social media profiles in order to build a personalised recommender framework. In the case of extracting topics from textual data, the topic modelling technique is used. Further-more, user-profile features are drawn from apps the user has in order to better understand their preferred apps. Personalized app ratings take both the interests and app functionality into account Results collected in the 'real world' are used to conduct tests, which suggest that customised app reviews have meaning.

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