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Comprehensive Analysis for Intelligent Recommendation on Mobile Applications

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Abstract. With the development of mobile devices and mobile apps, corresponding app recommendation analysis has received increasing focus in recent years. Such recommendation analysis covers aims including app evaluation, API-based app development, customer investigation, app security, etc. Meanwhile, various types of recommendation techniques are exploited in the app recommendation analysis, which continually improves the development of this direction. However, there is still a lack of a systematical study providing an overall development picture for these app recommendation efforts. Thus, it faces an obstacle for related researchers following this direction of work, and correspondingly is not conducive to the future development. To overcome the problem, in this paper, we take the first step to systematically investigate this direction of efforts. To this end, we summary the main works and techniques used in more than 35 important works in this direction. To better understand the development routines, we have analyzed the characteristics of these works from two perspectives, i.e., technology and research scenario. We have obtained some interesting conclusions within this research direction, and put forward some work suggestions according to the overall research.

Keywords: recommendation system, mobile App, software analysis, deep learning, android permission

1. Introduction

With the development of mobile devices and applications, corresponding application recommendation analysis has attracted more and more attention in recent years. Such recommendation analysis covers aims including app evaluation, API-based app development, customer investigation, app security, etc.

These analysis works are of great significance to the improvement of mobile application technology and the expansion of application scope. They can use advanced intelligent learning technology to reduce the human factor in software quality. For example, application intelligence recommendation in the mobile market provides valuable advice for users to choose the required applications. API-based app code recommendation felicitates the code construction for app development. Permission recommendation for mobile applications is a specific supplement to the security experiences of ordinary application users. In this process, various types of recommendation technologies have been developed into app recommendation analysis, and the development of this direction has been continuously improved.

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These technologies not only include the traditional recommendation system models, but also include some advanced intelligent learning algorithms, which can be introduced into the field of app recommendation. Among them, user/project collaborative filtering, matrix decomposition and factorization machine are traditional recommendation technologies, which can be applied to relatively wide range of scenarios, but there are limitations in the recommendation performance. However, the recommendation model based on deep learning, such as graphical neural network, significantly improve the recommendation accuracy, but consumes a lot of computing resources. It can be seen that the current research on mobile application recommendation systems is ubiquitous.

However, there is still a lack of a systematical study providing an overall development picture for these app recommendation efforts. Therefore, it faces an obstacle, and the related researchers following this direction, which is correspondingly unfavorable for future development.

Since app related recommendation research work involves diverse fine-grained application fields, it is challenging to give an overall picture to present the development routines for them. Furthermore, the related technologies used in these works are quite different. Correspondingly, how to comprehensively display these technologies and related application topics is also a big problem. To overcome the problem, in this paper, we take the first step to systematically investigate this direction of efforts. To this end, we have summarized the main works and using skills of over 35 important works in this direction. In order to better understand the development process, we analyzed the characteristics of these works from the perspectives of technology and research scenes. We have discussed the main characteristics of the study and achieved some interesting conclusions within this research direction. We expect this work to provide substantial support for the future improvement of the recommendation system targeting mobile apps.

2. Multi-dimensional study for intelligent recommendation of mobile Apps

Table 1. Representative works in recommendation for mobile Apps (continue).

Scenario	Work	Contribution	Technology
Recommendation for mobile device application	Huitzil et al. [1]	Infer implicit knowledge	fuzzy logic and semantic reasoner
Android API Recommendation	Library guru by Yuan et al. [2]	Recommend both functional and overridden APIs	customized parsing of code snippets and NLP
Recommendation for movies and music	Lee et al. [3]	Obtain available data from mobile devices to recommend items and products	collaborative filtering, Bayesian hybrid recommendation system
Health recommendation	Ertuğrul et al. [4]	Treat patients based on their personal data and collected medical data, semantic-based personalized recommendation	knowledge-based RS, expert decision support systems, electronic/mobile health systems, IoT applications

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Table 2. (continued).

Recommend for accessibility features in consumer OS	Wu et al. [5]	Research how to help the disabled find accessibility features on mobile devices	collaborative filtering, recommend auxiliary functions based on how the user interacts with the device, automatic/prototype recommendation
App Recommendation	sparse additive generative model (Mobi-SAGE) by Yin et al. [6]	Personalized app recommendations using category-aware user privacy preferences and multimodal app content data	By considering both user interests and category-aware user privacy preferences
Children education	Smart library by Almudena et al. [7]	Increase their engagement and the diversity of apps that users use	recommends content to child users, and provides feedback for parents and educators
App recommendation	MV-AFM by Liang et al. [8]	models the interactions of features from different views	Multi-view factorization machines & hierarchical attention
Food recommendation	FooDroid by Runo [9]	Recommend available menus based on the preferences of the user	User-based Collaborative Filtering.
App recommendation	SUCM model by Liu etal. [10]	develop a structural user choice model to learn fine-grained user preferences among apps	Hierarchical Softmax
Cross-version app recommendation	Lin et al. [11]	incorporates features distilled from version descriptions into app recommendation	semi-supervised topic model & version-sensitive ranking
App recommendation	Peng et al. [12]	take account of apps' permissions, functionalities and users' interests altogether	matrix factorization algorithm based on users' interests and apps' permissions
Cross-version app recommendation	Cao et al. [13]	alleviating the data sparsity problem caused by version division	matrix factorization based version evolution recommendation

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Table 3. (continued).

Cross-platform app recommendation	STAR model by Cao et al. [14]	integrates both numerical ratings and textual content from multiple platforms	Cross-Platform Matrix Factorization Model
App recommendations	Liu et al. [15]	trade-off between functionality and user privacy preference	improved Poisson distribution based prediction model
App recommendations	Kim et al. [16]	considering semantic relations between apps	Ontology, similarity concept
App recommendations	Actual Tempting model by Yin et al. [17]	contest between the owned apps' actual values and the candidate app's tempting value	probability model learning and ranking algorithm
Cold-start in app recommendation	Lin et al. [18]	Twitter account based pseudo-documents and latent group mapping	Latent Dirichlet Allocation
Permission requirements recommendation	CLAP by Liu et al. [19]	mining potential explanations from the descriptions of similar apps	information retrieval, text summarization, similarity computation, and frequent permission analysis
Cross-platform recommendation	Liang et al. [20]	investigating the spillover effect on editor recommendation	regression model, two-stage bivariate probit model
App recommendations	He et al. [21]	combining download and browsing behaviors	LDA-based graphic model
Library recommendation	GRec by Li et al. [22]	improved Third-party libraries recommendation	graph neural network
App recommendation	Liang et al. [23]	fully exploit both structural and feature information	heterogeneous graph neural network, node-level attention
Cross-Domain recommendation	Ouyang et al. [24]	balance the weight of each domain and efficiently train the model	Multi-graph neural network

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Table 4. (continued).

location recommendation	interval valued intuitionistic fuzzy sets by Oner. et al. [25]	Meet the needs of location-based services	intuitionistic fuzzy similarity matrix based collaborative filtering
exercise learning recommendation	Xia et al. [26]	Consider the coverage and knowledge level of exercisers' knowledge points to help them find appropriate exercises.	sports recommendation algorithm
App recommendation	Bae et al. [27]	Used for app recommendation in the Android OS environment.	Graphics-based AppTrends
Minimum Permission requirements recommendation	MPDroid by Xiao et al. [28]	Assess over-privilege risk by examining the application's additional permissions to limit unnecessary permissions requested	static analysis and collaborative filtering
API Documentation Repair Recommendations	DRONE by Zhou et al. [29]	Detect and fix API documentation in case of defects	prototype repair recommendation system
Android API Recommendation	Gao et al. [30]	summarizing API usage for the same or similar functionality in the application for API recommendations	A mapping relationship between functions and APIs, A framework for the same class of functions search
Minimum Permission requirements recommendation	RecDroid by Rashidi B, Fung C, Vu [31]	A ranking algorithm is used to assess the user's level of expertise, and a voting algorithm is used to calculate the appropriate response (accept or deny) to permission requests	Ranking Algorithm, Voting Algorithm, Crowdsourcing Recommendation Framework
Cross-Domain recommendation	p-PLIERS by Arnaboldi et al. [32]	Ability to discover and select content of interest to individual mobile users in a highly personalized way	Recommender system based on PLIERS tags

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Table 5. (continued).

Recommend custom resources to categorized user types	Park et al. [33]	Reduce referral time for small mobile devices with limited resources	Based on Myers-Briggs type metrics / A method for recommending customized resources for classified user types
Avoid Information Leaks on Android	SARRE by Li et al. [34]	SARRE prevents information leakage and protects private data with very little performance overhead.	Statistical analysis and minimum path coverage algorithms, dynamic runtime monitoring, prototyping
Permissions required for the recommendation API	Bao et al. [35]	Produces significant improvements in precision, recall, F1-score, and MAP of top-k results when recommending the required permissions for the API	Collaborative filtering , text mining technology: Naive Bayesian Polynomial Classification Algorithm
Recommended code for Android development	Wu et al. [36]	Ensuring high Android application development efficiency and quality	A customizable tool framework
App recommendation	DroidVisor by Rustgi et al. [37]	Similarity to pre-selected target apps is considered, and other metrics such as popularity, security, and usability are also considered.	Provide users with fine-grained, recommended algorithms, use case studies

In recent years, the recommendation of mobile applications is developing day by day. Especially, the research scenarios are gradually extended. Most of the early works were aimed at the recommendation of ordinary apps [6,8,12,15-17,21,23, 27]. For instance, Yin et al. employ user's personal resources, such as location [6], messages, and contacts to conduct the app recommendation, where they think such resources affect the user's desire to download the app. Liang et al. proposed MV-AFM which exploits multi-view factorization machine models the interactions of features from different views [8]. To further improve the recommendation accuracy, the hierarchical attention is integrated into the original AFM model. Peng et al. employ the app permission information besides user interests to conduct the recommendation [12], where the matrix factorization algorithms are utilized. Liu et al. improve Poisson distribution based prediction model to trade-off between functionality and user privacy preference [15]. Kim et al. adopt ontology techniques to construct the semantic ontology graph, which considers semantic relations between apps [16], and use the similarity concept to compute the recommendation score of each app. Yin et al. proposed a novel actual tempting model which is based on probability model [17]. The model sufficiently contests between the owned apps' actual values and the candidate app's tempting value. Then the ranking algorithm is applied to rank the recommendation list from the learned candidates. He et al. use LDA-based graphic model to combine the download and browsing behaviors [21], which evaluate the recommendation accordance in a

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comprehensive way. Liang et al. introduce the heterogeneous graph neural network into the app recommendation which fully exploits both structural and feature information [23]. Bae et al. uses a graphics-based technique for application recommendation in the Android OS environment [27]. Rustgi et al. propose an Android tool called DroidVisor [37], which aims to recommend apps for users taking into account similarity to pre-selected target apps and safety features or user preferences. Generally speaking, the goal of these application recommendation work is to provide better application recommendation model for mobile users. These improvements mainly come from the development of technology and the diversification of data materials.

Some work is aimed at recommending suitable Android API for functional requirements of target apps. For instance, Yuan et al. proposed LibraryGuru, an API recommendation framework for event-driven Android programming [2]. The framework is developed to recommend both functionality implementation of target APIs and the event callback mechanism of overridden APIs. Li et al. proposed GRec, a graph neural network based recommendation framework that can improve the third-party libraries recommendation [21]. Zhou et al. propose a prototype repair recommendation system that detects and repairs API documents when there are defects [29]. Gao S et al. build a framework that describes the functionality of applications of the same category and provide an API recommendation method for the development of Android applications [30]. Bao et al. utilizes collaborative filtering and text mining techniques to better recommend the permissions required by the API [35]. To this end, the third-party libraries are first constructed altogether as a function call graph, and the neural network algorithm is learned on the features indicated in the graph nodes.As the graphic neural network extracts more fine-grained features, the recommendation accuracy is improved accordingly.

Partial works concentrate on the recommendation between the cross-version apps. For instance, Lin et al. exploit semi-supervised topic model to incorporate features distilled from version descriptions into app recommendation [11]. They also propose a version-sensitive ranking algorithm to adapt the topic model into version-aware app recommendation. Cao et al. alleviate the data sparsity problem caused by version division by matrix factorization based version evolution recommendation [13].

To recommend the apps belonging to the cross-platform or domain, Cao et al. [14] proposed STAR model, where the matrix factorization is used to integrate both numerical ratings and textual content from multiple platforms. Liang et al. investigate the spillover effect on editor recommendation by regression model and two-stage bi-variate probability model [20]. Ouyang et al. use multi-graph neural network to balance the weight of each domain and efficiently train the model [24]. Arnaboldi et al. propose a PLIERS tag-based recommender system to discover and select content of interest to individual mobile users in a highly personalized way [32]. The effectiveness of the recommendation has been significantly improved.

In the recommendation for mobile devices, Alegre et al. extended the fuzzy technique for the ontology with elements and explored novel fuzzy set theory [1]. Thus, Android mobile devices can be accurately recommended. To recommend suitable device item to users. Lee et al. proposed a context-aware Bayesian hybrid recommendation system that combines contextual information collected from mobile devices and user preferences [3]. Park et al. proposes a method for recommending customized resources for categorized user types to reduce recommendation time for small mobile devices [33]. By using the norm weight introduced by Campos, the complex problem of calculating the conditional distribution becomes a simple linear sum of weights.

In terms of other specific suggested targets, the related work has made remarkable progress in recent years. For example, Ertuğrul et al. recommend the health case information for users through learning the data collected from health care mobile apps [4]. Wu et al. investigate accessibility recommendations within mobile apps which provide other ways for people with various disabilities to access computing devices [5]. Almudena et al. improve user engagement and children's experience on a mobile EdTech platform through a typical recommender system by the number of games and play time [7]. Liu et al. aim to permission recommendation through app analysis [19]. Xiao et al. propose a method named MPDroid that combines static analysis and collaborative filtering to alleviate Android

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app permission overuse [28]. They proposed CLAP, which uses information retrieval, text summarization, similarity computation, and frequent permission analysis to mine the potential explanations from the descriptions of similar apps. Rashidi et al. proposed a crowdsourced recommendation framework called RecDroid to help users make the right decision on whether to accept permission requests [31]. Lin et al. aim to alleviate the cold-start problem within the app recommendation [18]. To this end, they introduced the Latent Dirichlet Allocation (LDA) algorithm to the app recommendation and proposed a Twitter account based pseudo-documents and latent group mapping algorithm to recommend the new added app items from its group relationship. Runo proposed FooDroid, a recommendation model to recommend food for app users [9]. The author adopts the traditional user-based collaborative filtering to recommend available menus based on the preferences of users. Oner, S. C. et al. proposes an intuitive fuzzy restaurant location recommendation system based on the interval value of social platforms [25]. Xia J, Li G, Cao Z studies an exercise recommendation algorithm that combines learning objectives with exercise result feedback [26]. Li et al. propose the SARRE system for preventing information leakage on Android [34]. Wu et al. present a set of improvement suggestions and a customizable tool framework to recommend code for Android development [36].

3. Methodology analysis for related recommendation works

In recent years, application recommendation and related topics for mobile systems have been continuously researched. In these work, various methods and technologies have been adopted or improved. In this section, we describe these involved methodologies and map them into the works. Therefore, it provides a general road map for future work.

3.1. User/Item-based collaborative filtering

The neighborhood-based collaborative filtering algorithm should be one of the most basic algorithms in the recommendation system, mainly including user-based collaborative filtering and item-based collaborative filtering. Given the behavior data, the recommendation is to find the users who are the most similar to him, because they have similar features. Another method is to find the product that are most similar to those that the user have interacted with in history. The user has liked it before, and may like something similar or related to it.

3.2. Matrix factorization

Matrix factorization is to predict the missing value in the rating matrix, and then recommend it to the user in some way based on the predicted value. Common matrix factorization methods include basic matrix factorization (basic MF), regularized matrix factorization (Regularized MF), probability-based matrix factorization (PMF), etc.

3.3. Factorization machine

Factorization machine was first proposed by Steffen Rendle in 2010, aiming at solving the problem of feature combination under large-scale sparse data. The factorization machine considers the influence of the second-order combined feature $x_i \cdot x_j$ or the third-order combined feature on the target value, as shown by the following equation.

$$\hat{y}(x) := w_0 + \sum_{i=1}^{n} w_i x_i + \sum_{i=1}^{n} \sum_{j=i+1}^{n} < V_i, V_j > x_i x_j \quad (1)$$

where $< v_i \cdot v_j >$ represents is the dot product of the k dimensional vectors v_i and v_j, also corresponding to a real value.

$$< \boldsymbol{v}_i \cdot \boldsymbol{v}_j > := \sum_{f=1}^{k} v_{i,f} \cdot v_{j,f} \quad (2)$$

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3.4. Latent dirichlet allocation (LDA)

LDA was proposed by David Blei, Andrew Ng and Michael I. Jordan in 2003. Because of the simplicity and effectiveness of the model, it set off a wave of topic model research. The construction of LDA includes five typical steps: 1) the computation of gamma function; 2) the construction of four distributions: binomial, multinomial, beta, Dirichlet; 3) the construction of Conjugate Priors and Bayesian Framework; 4) the building of pLSA model and 5) data processing by Gibbs sampling.

3.5. Graph neural network model

Graph Neural Network (Graph Neutral Networks, GNNs) is a deep learning method based on graph structure. From its definition, it can be seen that graph neural network is mainly composed of two parts, namely "graph" and "neural network". The "graph" here is the graph data structure in graph theory, and the "neural network" is the deep learning NN structure we are familiar with, such as MLP, CNN, RNN, etc. The current classic and popular GNN networks include GCN, GraphSAGE, GAT, GAE, and graph pooling strategy DiffPool. Compared with traditional neural networks, graph neural networks has obvious advantages. 1) Non-sequential feature learning: The output of GNNs is not transitioned to the input order of nodes. 2) Learning of dependencies between two nodes: In traditional neural networks, this dependency can only be represented by the features of nodes. 3) Reasoning ability: GNN can generate reasoning graphs from unstructured data.

3.6. Other methodologies

In addition to the mainstream technology used in existing works, there are other methods. For instance, Huitzil et al. [1] uses fuzzy ontology to represent related knowledge and semantic reasoners to infer implicit knowledge. Even when the information is incomplete, it uses quantifier-guided aggregation to provide suggestions. Some works introduce the techniques of NLP (Natural Language Processing) into the app related recommendation. For instance, the LibraryGuru of Yuan et al. [2] implement an xml textual parsing and similarity matching algorithm, which extracts co-relationship pairs from Android SDK reference and computing corresponding TF/IDF. Ertuğrul et al. [4] introduced the semantic web and health related word embedding into the app recommendation for personalized health enhancement. Yin et al. [6] leverage application-related textual and visual content to learn multi-view topics for user interest modeling. The approach is evaluated on a large-scale real dataset is collected from the 360 App Store. Almudena et al. [7] also exploit NLP word embedding to represent the textual information for improving children's experience on a mobile EdTech platform.

4. Discussion for App-oriented recommendation

From the analysis and research of app recommendation on mobile systems, the development of this research direction has the following features.

First of all, the development of the app recommendation is generally accompanied by the development of related technologies of recommendation system. For instance, the early works tends to apply the traditional collaborative filtering, matrix factorization and factorization machine to implement related recommendation work. In recent years, with the development of deep learning and corresponding recommendation technology, the recommendation based on deep model has been gradually introduced into the improvement of related recommendations of mobile app. And it can be seen that the future development in this work direction would also be motivated by advanced or newly proposed recommendation techniques.

Secondly, although most related works aims at providing advanced application recommendation models, there are still related efforts to explore novel topics. These efforts have resolved the challenges including of API recommendation, user reviews analysis, cold start problem and cross platform problem. In the future work, there will be more premising related novel problems being explored around the direction.

Third, the data materials applied in the recommendation process are gradually extended. In the early efforts, application recommendation mainly depended on the basic functions in the application

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market, such as the user downloads, application ratings and application installations. With the development of this direction, the data materials already involve peripheral features, such as user comments, cross-platform information, authority data, version data, etc. In order to solve more challenging problems in the future, it is expected to explore diversified types of data materials.

5. Conclusion

In this paper, we conduct a systematical study on the recommendation efforts for mobile apps. This work has provided some valuable information for the future work in this direction. We investigated more than 35 recent related works in detail, and found out the working features of these works from the perspectives of technology and research scenes. According to the full research on this direction, we find that the recent efforts tend to use advanced learning technology to improve the effectiveness of app-related recommendations. In addition, some interesting conclusions are discussed accordingly.

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