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Interoperability-Enriched App Recommendation

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***Abstract*—At present, there are three main mobile apps marketplaces, iTunes App Store, Google Play and Windows Phone Store. With app recommendation technology, users not only discover more relevant apps, but they're also more likely to be engaged with those apps on a higher level because they are relevant to their interests in the first place. Collaborative filtering (CF) methods had been applied to recommender systems, but the CF techniques do not handle sparse dataset well, especially in the case of the cold start problem where there is no enough interaction for apps. To conquer this constraint, we propose a novel recommending model: Interoperability-Enriched Recommendation (IER) that is an interoperability-enriched collaborative filtering method for multi-marketplace app recommendation based on the global app ecosystem. Experimental results on the known marketplaces app dataset demonstrate that the proposed IER method significantly outperforms the state-of-the-art CF method and context-aware recommendations (CAR) method for app recommendation, especially in the cold start scenario.**

Keywords- Mobile Apps; App recommendation; Collaborative Filtering; Interoperability-Enriched; Cold Start

I. INTRODUCTION

Mobile apps for these marketplaces are all growing at phenomenal rates. With iTunes now carrying 1,200,000 apps in its store, Google Play carrying 1,250,000, and Windows Phone Store up to more than 120,000 certified apps[1], it's no wonder users have turned to app recommender system in the official vendor-specific app stores. With app recommendation technology, users not only discover more relevant apps, but they're also more likely to be engaged with those apps on a higher level because they are relevant to their interests in the first place. To the mobile publishers, it's a unique opportunity to monetize their mobile content or mobile app through recommending related apps for users to install on their devices.

For example[2], Figure 1 shows that from Jan 2012 to May 2014, Android continued to lead the market, the iPhone saw a cyclical decline leading up to the iPhone 5C/5S launch and Windows Phone continued to grow at a smaller scale. Android's usage share has been growing while that for the iPhone has declined slightly. This should be expected as Android's shipments and install base have been growing much faster than those for the iPhone.

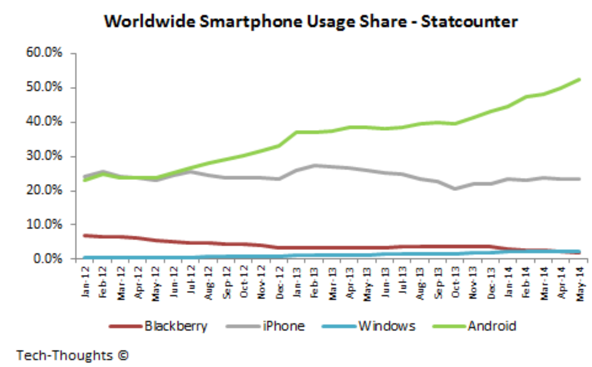

Figure 1. Worldwide smartphone usage share.

Recent research has shown that the tremendous increase of mobile apps has aroused the significant challenge of app discovery. Nevertheless, the development of recommender systems for mobile apps is at a slow pace. Collaborative filtering (CF) methods had been applied to recommender systems in the past years. However, it's very different to recommend items between online web information and mobile apps. Some performance-improved CF methods have been tried to make effective app ranking, such as item-based/user-based top-N recommendations, neighborhood-based CF. However, the recommendation is concurrently restricted to certain local scope of apps, as most users only access a limited amount of apps from certain mobile marketplace.

To conquer this constraint, we propose a novel recommending model: Interoperability-Enriched Recommendation (IER). The IER model is an interoperability-enriched collaborative filtering method for multi-marketplace app recommendation based on the global app ecosystem. We deal with the dual challenge of building an interoperability-enriched model in the absence of explicit interaction information from the user and incorporating mature app marketplaces information into the proposed recommendation model.

We conduct extensive experiments on real world app data sets from several known marketplaces and compare the IER method with the state-of-the-art CF method, such as

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[1] How Many Apps Are in the iPhone App Store. http://ipod.about.com

[2] Smartphone Market Share And Usage By Country - Apr-May 2014. http://www.tech-thoughts.net/

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item-based top-N recommendations (IBT), user-based top-N recommendations (UBT), neighborhood-based CF (NBCF), and context-aware recommendations (CAR). The experimental comparison result shows that our method significantly outperforms these techniques.

II. RELATEDWORK

Typical performance-improved CF recommendation mechanism is neighborhood-based CF and context-aware recommendations CF (e.g. Google Play market utilizes the user behaviors data to provide app recommendations). However, the CF techniques do not handle sparse dataset well, especially in the case of the cold start problem where there is no enough interaction for apps. When lack of such interaction, the CF recommendation is to either wait for sufficient review for ratings or use content-based filtering (CBF). The obvious drawback of CBF is that can only recommend apps with similar textual descriptions [1]. Some improved app recommendation methods are proposed [2], such as item-based top-N recommendations (IBT), user-based top-N recommendations (UBT), neighborhood-based CF (NBCF), and context-aware recommendations (CAR).

III. INTEROPERABILITY-ENRICHED RECOMMENDATION METHOD

Instead to use method based on user interaction or content comparison, we use ranking information from multi-marketplace to enrich performance of uninformed recommender, especially in the cold-start situation.

This Interoperability-Enriched Recommendation (IER) method creates a win-win situation for both ends of the spectrum—developers and users. Developers can lower their cost of marketing apps because they're marketed to the right people in the first place, but the end user also benefits because they're finding and using great apps with minimal effort to discover them. On the other hand, the IER method should create a win-win situation for each app marketplace by exploiting enriched interoperability information from the global app ecosystem.

A. *Interoperability-Enriched Ranking*

For the two largest mobile apps marketplaces, iTunes APP Store and Google Play, many providers simultaneously submit the same or similar apps to both marketplaces for their economic profit. However, for relatively smaller marketplaces, such as Windows Phone Store or BlackBerry APP World, there are less apps than iTunes and Android. In this situation lacking of rating (i.e., the cold-start), the disadvantages of CF techniques become more serious.

The main idea of the IER method is to decompose the interoperability into three matrices (see Figure 2): U (user), A (app) and M (Marketplace), using the Context-Aware model [3] which corresponds to learned factors that form a profile for each user, app, and context variable respectively (here context is marketplaces).

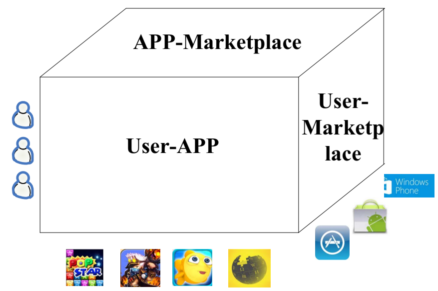

Figure 2. Interoperability between User, APP and Marketplace.

Assume m is the number of users, n is the number of apps and p is the number of marketplaces. The 3-dimensional interaction model illustrates the interoperability between the users, apps and the marketplaces (i.e. the number of times a user interacted with an app at a particular marketplace). An absence of an interaction is signaled with a 0.

User-APP interoperability: $I_{u,a} \in R^{m \times n}$;

APP-Marketplace interoperability: $I_{a,m} \in R^{n \times p}$;

User-Marketplace interoperability: $I_{u,m} \in R^{m \times p}$.

The ranking function that would provide a score for the recommendation engine for a user u_i, app a_j, marketplace m_k is given by

$$R_{i,j,k} = \left\langle I_{u_i,a_j}, I_{a_j,m_k}, I_{u_i,m_k} \right\rangle = \sum_{i,j,k} I_{u_i,a_j} I_{a_j,m_k} I_{u_i,m_k} \quad (1)$$

We take into account the confidence of three factors also, i.e. an app that is downloaded and reviewed more times should has greater confidence, an user that reviewed more apps should has greater confidence, and a marketplace that has more apps should has greater confidence. We set the confidence for ranking score r_{iik} as ω_{iik} given by:

$$\omega_{ijk} = \alpha \log(1 + \frac{m}{m^{a_j} + 1}) + \beta \log(1 + \frac{n}{n^{u_i} + 1}) + \gamma \log(1 + \frac{n}{n^{m_k} + 1}) \quad (2)$$

Where m^{a_j} is the number of users who had downloaded or reviewed app a_j, n^{u_i} is the number of apps downloaded and reviewed by user u_i, and n^{m_k} is the number of apps of marketplace m_k. We set the parameter α, β, γ to 0.3, 0.2 and 0.5 for all our experiments.

Then we compute these factors by minimizing the following objective function:

$$\min_{U,A,M}\sum_{i}\sum_{j}\sum_{k}[\omega_{ijk}(r_{ijk}-\langle I_{u_i,a_j},I_{a_j,m_k},I_{u_i,m_k}\rangle)^2 + \frac{\lambda}{m}\|U_{i*}\|^2+\frac{\lambda}{n}\|A_{i*}\|^2+\frac{\lambda}{p}\|M_{i*}\|^2] \quad (3)$$

The right part term $\frac{\lambda}{m}\|U_{i*}\|^2+\frac{\lambda}{n}\|A_{i*}\|^2+\frac{\lambda}{p}\|M_{i*}\|^2$ in the objective function is required for regularization.

B. *Interoperability-Enriched Recommendation*

App developers commonly write multiple versions of the same app for different mobile platforms, although the developer has to create entirely separate sets of code in two entirely different programming languages. For example, we can get Facebook, Twitter, The Weather Channel, Bump and hundreds of other apps for both iPhone and Android. The two apps may look the same, walk the same and quack the same when used on different phones, but in developers' eyes they are completely different. Fortunately, in users' eyes they are equally important for app recommendation. For this reason, in the emerging marketplace (i.e. Windows Phone Store), we can easily identify the same or similar app from several leading marketplace (i.e. iTunes APP Store and Google Play).

Our approach is based on a "weighted averaging" method where the ranking score of the candidate app list for the target user will is calculated according to the weighted averaging score of the related app list.

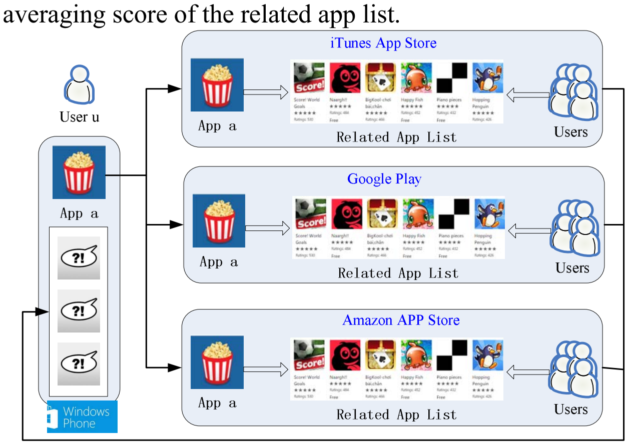

Figure 3. The interoperability-enriched recommendation based on a "weighted averaging" method.

Given a set of marketplaces M, the ranking score of the candidate app is defined as follows:

$$Score(a,u)=\sum_{a\in M(a)}\omega_m\sum_{u\in M(m,u)}r_{u,a} \quad (4)$$

Where

- Score(a, u) is the ranking score of app 'a' to be recommended for the target user 'u';
- ω_m is the weighted coefficient of marketplace 'm';
- M(a) is the set of marketplaces containing app 'a';
- M(m, u) is the set of users in marketplace 'm';
- $r_{u,a}$ is the ranking score calculated by neighborhood-based algorithm.

Specifically, $r_{u,a}$ can be calculated as:

$$r_{u,a}=\frac{\sum_{u'\in R(a)} sim(u,u')r_{u',a}}{\sum_{u'\in R(a)} sim(u,u')} \quad (5)$$

Where $sim(u,u')$ is the similarity of user u and u'.

As a result, we can give the target user the recommended app list by the ranking score.

IV. PERFORMANCE EVALUATION

In this section, we evaluate the performances of IEP method using real-world App data.

A. *Interoperability-Enriched Dataset*

We constructed our dataset by crawling from Apple's iTunes App Store, Google Play and Amazon App Store in May 2014. Altogether, we collected 736,377 apps.

B. *Test Dataset*

Wpapps marketplace[3] recommends mobile apps to its users covering the whole platform of Windows Phone (WP). Its key features include downloading, managing and recommend apps of WP. In total, the wpapps dataset contains 30,000 users, 250,000 apps and ten millions of log items about the usage of apps. Currently, the wpapps marketplace hasn't applied IEP method to its app recommender.

In our experiment, the IER method outputs k apps for each test user, which are sorted by their ranking score. We evaluate the algorithms based on interoperability-enriched dataset constructed in section 4.1.

Firstly, we randomly select 1000 additional apps with a few of interaction with users in wpapps marketplace. We predict the ranking scores of the test apps for user u. Then we generate a candidate app list by ranking the selected apps according to their ranking scores. This candidate app lists over all users are then used to produce Precision-Recall plots.

C. *Experimental Comparison*

The goal of our experiments is to compare the performance of IER with the state-of-the-art CF method, such as item-based top-N recommendations (IBT), user-based top-N recommendations (UBT), neighborhood-based CF (NBCF), and context-aware recommendations (CAR).

Figure 4 shows the results of the contrastive experiment, which compares the overall performance when we vary the number of recommended apps k from 10 to 120.

[3] Dapai App Marketplace for Windows Phone. http://www.wpapps.com.cn/

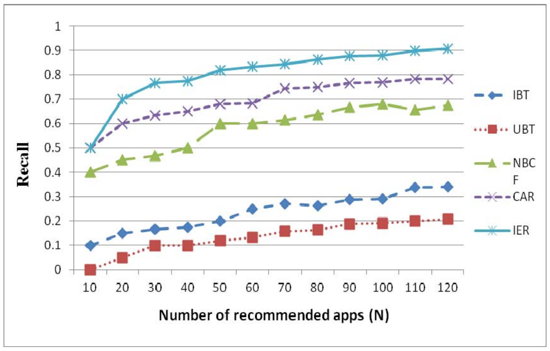

Figure 4. The results of the contrastive experiment when vary the number of recommended apps k from 10 to 120.

In the overall comparison over all ranges of N, the IER method consistently achieves better performance than the other CF methods. From a practical standpoint, it's easy to understand that the IBT and UBT get the poor performance in our experiment scenario, where there is the cold-start problem. The NBCF method gets the modest performance because it makes use of the interaction between users and apps.

Carrying out a more detailed inspection, we find that app context give limited improvement about the app's informative recommendation with 70% recall, and the CAR method still is a good app recommendation algorithm relatively. From the comparison, it clearly indicates significant benefits of using interoperability-enriched in multi-marketplace for app recommendations.

V. CONCLUSIONS

With app recommendation technology, users not only discover more relevant apps, but they're also more likely to be engaged with those apps on a higher level because they are relevant to their interests in the first place. To the mobile publishers, it's a unique opportunity to monetize their mobile content or mobile app through recommending related apps for users to install on their devices. Collaborative filtering (CF) methods had been applied to recommender systems in the past years. Some performance-improved CF methods have been tried to make effective app ranking, such as item-based/user-based top-N recommendations, neighborhood-based CF.

However, the recommendation is concurrently restricted to certain local scope of apps, as most users only access a limited amount of apps from certain mobile marketplace. Recommendation from places users trust has mostly remained decentralization and spread through all over the apps ecosystem.

To conquer this constraint, we propose a novel recommending model: Interoperability-Enriched Recommendation (IER). The IER model is an interoperability-enriched collaborative filtering method for multi-marketplace app recommendation based on the global app ecosystem. We deal with the dual challenge of building a interoperability-enriched model in the absence of explicit interaction information from the user and incorporating mature app marketplaces information into the proposed recommendation model.

Experimental results on the real-world app data sets demonstrate that the proposed IER method significantly outperforms existing methods for app recommendation and ranking, especially in the cold start scenario.

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