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Procedia Computer Science 110 (2017) 236–241

Procedia Computer Science

www.elsevier.com/locate/procedia

The 14th International Conference on Mobile Systems and Pervasive Computing (MobiSPC 2017)

Recommendation of Mobile Applications based on social and contextual user information

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Abstract

Recommendation Systems of Applications (RSA) are based on various types of user information. Some of these systems analyze the influence of social networks information in the installation of apps. However, these approaches do not include all the relevant user information. The present paper proposes a technique for recommending mobile applications based on a social and context information. The approach is compared with two existing techniques showing improvements in the recommendation quality and high tolerance to a small number of data.

Peer-review under responsibility of the Conference Program Chairs.

Keywords: Mobile Application Recommender Systems, Context-Aware Systems, Implicit Feedback, Social Networks

1. Introduction

Given the large number of existing apps (mobile applications), it may become hard to find an appropriate app for a particular purpose. The recommendation systems of applications (RSA) have emerged to address this problem, offering personalized recommendations to the users[3]. In this context, it has been demonstrated that the installation of apps can be influenced by the user's context[7] and the Social Networks[9].

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1877-0509
Peer-review under responsibility of the Conference Program Chairs.
10.1016/j.procs.2017.06.090

Some approaches include both applications popularity and user security preferences to develop a flexible RSA[10]. Other works have studied the impact of mobile social networks in app installation.

The authors aim at finding the most influential users by using a Community-based Greedy algorithm[11]. Unlike the previous approaches, the present paper presents a recommender system called

Vanilla that includes both social and context information. The rest of this paper is organized as follows Section 2 describes Vanilla. Section 3 presents the experimental evaluation, and Section 4 concludes.

2. Description of Vanilla approach

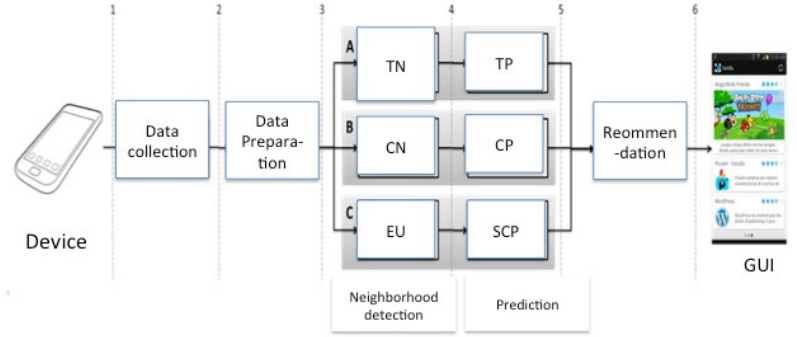

Figure 1. Vanilla overall process

Figure 1 describes the main components of Vanilla. The *mobile device* is the primary source of information that gathers the necessary information for the consumption analysis. The *data collection* and *data preparation* components receive the consumption information and generate an overall app rating (*V-FPR)*, a context-aware app rating (*V-FPR-C) and* a set of categories according to the current user´s context. The *neighborhood detection*, *prediction,* and *recommendation* components support the comparison of three recommendation approaches: traditional (branch A: traditional neighborhood – TN and traditional prediction- TP), contextual (branch B : contextual neighborhood – CN and contextual prediction - CP) and *Social-Contextual Vanilla* (*V-SCR* in branch C: Expert users – EU and Social contextual prediction - SCP), as presented in Figure 1. Vanilla integrates a work-based scheme[6] that supports the evaluation of multiple recommendation techniques simultaneously with a single interface. This last feature is included in the recommendation component. A description of the modules is presented below.

2.1. Data collection

This module collects information about the application lifecycle and the[14]. This component monitors the change in 11 dimensions (see table 1) 9 of these are collected automatically, and 2 require user intervention.

Table 1. Contextual Dimensions

Contextual Dimension	Source of Information	Context
Relative Location	User	Physical
Frame of Mind	User	Cognitive
Orientation	Smartphone	Physical
Time	Smartphone	Physical
Lighting	Smartphone	Physical
Movement	Smartphone	Physical
Position	Smartphone	Physical
Weather	Web Service	Physical

To model and analyze these dimensions, the following variables are defined

$$V = \{v_i\}_{1 \le i \le n} \quad , \quad S_i = \{s_{i,j}\}_{1 \le j \le m} \quad , \quad c = \{s_{i,*}\}_{1 \le i \le n} \tag{1}$$