Context-Aware Multimedia Content Recommendations for Smartphone Users

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INTRODUCTION

According to Gartner, a world leading information technology research and advisory company, 57.6% of all *mobile phones* sold in the last quarter of 2013 were *smartphones* (Gartner, 2013). Unlike feature phones, smartphones are replacing our desktops as they increasingly become more powerful in terms of processing capability, network connectivity, and multimedia processing support (Flora, 2010; Ricci, 2011). This development indicates global penetration and acceptance of smartphones as the primary platform for information access and processing.

As mobile users go about their daily activities, they continuously browse the Web, seeking interesting Web-based multimedia content to consume, and occasionally also uploading their personal content. However, these users encounter huge volume of available Web-based content, which often does not match their preferences. These preferences change as mobile users move from one place to another, performing different activities. Therefore, it is important to keep track and learn mobile user's contexts in which they perform such activities. This contextual information can be used to filter and to deliver relevant and interesting multimedia content, thereby assisting users to overcome frustrations of selecting from overwhelming set of potential multimedia content choices. Consequently, users can focus more on important activities, minimizing distractions and time wasted while browsing Web-based media.

Context-aware recommendation (CARS) has become a major focus of researchers addressing information overload related problems (Adomavicius et. al., 2005). This process can suggest multimedia content to mobile users by considering user's preferences and contexts in which such preferences are expressed. Many solutions of this kind, however, are limited to using static and explicit *contextual information*. For example, they rely on asking users to explicitly provide their current contexts in order to provide them with relevant items.. In fact, traditional recommendation systems do not consider context as an important factor in the recommendation process because they assume that user preferences are static. We define context-aware mobile multimedia recommendation (CAMR) as a special type of context-aware recommendations that uses mobile user's contexts to compute media recommendations.

CAMR is grounded in existing solutions and technologies. First, rapid development in the field of mobile and telecommunication networks has enabled ubiquitous communications whereby smartphone users can connect to the Web anywhere, anytime. With this development, mobile users can access multimedia content such as news, music, videos, etc. at their convenience. Second, mobile devices now come with cheap, built-in sensors, enabling ubiquitous context sensing (Kwapisz et. al., 2010). Sensors such as thermometers for sensing environment temperature, accelerometer for sensing movement, and GPS sensor for sensing location information, etc. now ship with smartphones. Third, context-awareness has enabled the ability to deliver personalized information based on user's contextual situations. Information such as location, activity, time, weather, etc. can now be obtained readily in real-time from smartphones. Fourth, traditional information recommendation systems have matured, and are helping users to find relevant information (Adomavicius et. al., 2005). Thus these existing solutions can be explored to realize context-aware mobile multimedia recommendations. Therefore, CAMR builds on these core solutions, using mobile user's preferences to suggest useful and interesting multimedia content, tailored to users contextual situations.

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Let us consider a scenario to illustrate this concept.

Sitting at home on a Friday at 8:30 PM, Ana enjoys watching video clips of latest movies on her smartphone. She relies on the system to provide her with favorite recommendations, especially latest movies that would interest her and her friends, as they plan to go to the cinema next Saturday evening. She prefers to have such suggestion when she engages in a less demanding activity, such as when she is relaxing at home, playing with her smartphone!

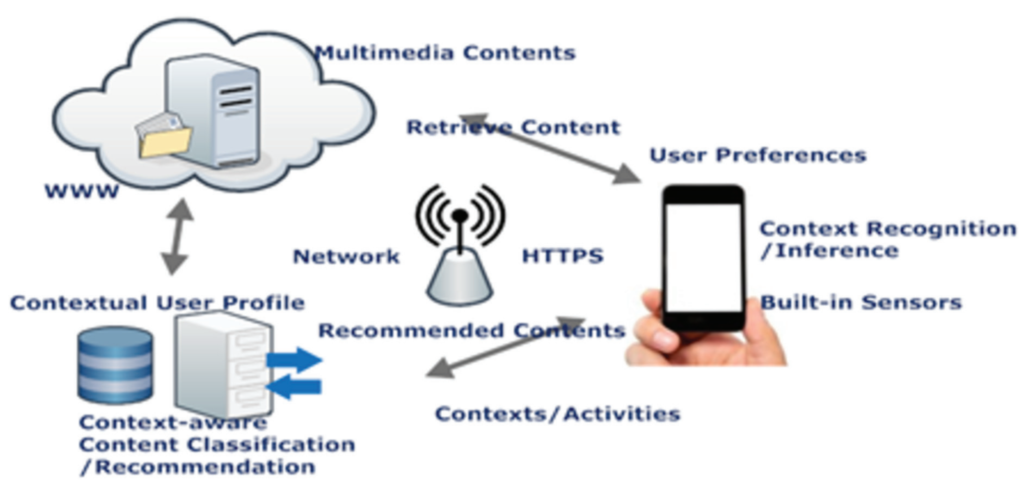
In this scenario, it is important to capture Ana's activities such as sitting, time of the activity, 8:30 pm, preferably at a higher level of inference, such as evening. Ana's location should also be inferred from GPS or Wi-Fi. CAMR should be able to obtain this information dynamically and use it to suggest relevant movies to Ana. CAMR has the potential to address these issues. Figure 1 illustrates a simplified architecture of CAMR. This article presents CAMR, a system that can suggest Web-based multimedia content to mobile users, using context recognition, contextual user profiling, and a context-aware content-based collaborative recommendation process.

BACKGROUND

Traditional recommendation techniques aim at guiding users to the most relevant items but do not take contextual information into account (Adomavicius et. al., 2005). These traditional recommendation techniques can be broadly categorized into three (Adomavicius & Tuzhilin, 2005): 1) based on the opinions and preferences of other users, designated as Collaborative Filtering (CF) (Schafer et. al., 2007); 2) based on user's consumption history and the descriptions of available candidate items, referred to as Content Based Recommendation (CBF) (Pizzani & Billsus, 1997); and 3) based on a combination of CF and CBF denoted as Hybrid Recommenders (HR).

Collaborative recommendation system traditionally predicts items to target users based on how similar users previously rated the same items. Formally, rating *R (u, i)* is predicted based on rating *R (u', i)* given to the same item *i* by user *u'* who is similar to user *u* (Adomavicius & Tuzhilin, 2005). CF is broadly categorized into 2: Memory-based and model-based collaborative systems. The former uses heuristics to make predictions based on the entire collection of previously rated items, whereas the latter uses collection of previously rated items to learn a model to provide recommendations for users. Because they load the entire dataset into system's memory for processing, memory-based CF systems are computationally expensive, especially when a very large number of users or items are involved. On the other hand, model-based CF requires less computational resources, in addition to having fast response time. Memory-based CF, however, produces more accurate predictions than a model-based CF (Adomavicius & Tuzhilin, 2005). A good example of CF system is GroupLens (Resnick et. al., 1994).

Figure 1. CAMR simplified architecture



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