Matching Content to the Mobile User
Smart Recommendations for Pervasive TV and Video

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Abstract. *This publication presents our work on recommender systems for mobile audio-visual content. Our approach generates recommendations for media by extracting metadata and matching it with user-centric criteria such as mood preferences. We address the specific issues arising from mobility such as the need to minimize CPU-load, interaction complexity, as well as learning effort required from the user and the system.*

Key words: Recommender Systems, Content-based Filtering, Mobile TV and Video, Semantically Enriched EPGs.

1 Motivation

In recent years, the increasing multimedia capabilities of mobile devices have generated a strong momentum for information and entertainment services such as Mobile TV and video. Research studies have shown that dynamic contexts such as waiting and commuting are among the most common ones for mobile content consumption [1]. In such contexts, the average duration of watching is around five minutes, with the end-users' attention resources notoriously being short in supply. Consequently, mobile users are not willing to spend much time on selection or navigation activities [2]. Therefore, smart recommender systems that accelerate content access with personalized suggestions closely matching user interests can considerably improve the mobile media user experience.

2 Mobile Recommender System Description

Current approaches for automatized content recommendation mainly fall into two categories: collaborative[2] and content-based filtering[3]. We focused on a *content-based* filtering approach because of the specific requirements originating of mobile usage:

[1] This work was supported by the Austrian Government and the City of Vienna within the competence center program COMET. We would like to thank the Chair for Artificial Intelligence at the University Erlangen-Nürnberg for providing their recommender engine and support.

- **Low latency and high scalability.** The system must minimize interaction response times to allow for a fluid user experience, even under heavy load. Content-based approaches allow for precomputation of intermediate results (e.g. content feature vectors) and distribution of processing steps to the client and thus scale very well with a growing number of users.
- **Useful recommendations from the start.** The system should not require a training phase, but rather deliver meaningful results also for first-time users. Collaborative approaches have difficulties here as they rely on extensive profiles that have to be explicitly entered or implicitly learned.
- **Instant adjustability to changing user preferences.** The mobile user's interests tend to vary depending on mood and context, easily rendering the associated profile incomplete or wrong. The user thus needs to be able to directly specify content features i.e. keywords, mood or genre dimensions.

Our content-based recommender system utilizes text mining and NLU (natural language understanding) to extract and match key features from the EPG (electronic programme guide) metadata associated with the content. It addresses aforementioned mobility requirements and covers both unicast and broadcast (e.g. DVB-H) content delivery.

2.1 Key Components

The **Recommender Engine** has been originally developed for accessing live and on-demand content in home setups [3]. For specifying content preferences it accepts natural language text input as well as four percentage values reflecting user mood preferences for *fun*, *action*, *thrill* and *erotic*. The recommendation generation process itself consists of four key steps: 1) Extract topics found in text (using the so-called Dornseiff Lexicon for abstraction and classification on a higher level in German language), 2) Scan the text for emotions and relate them to topics on a valence/arousal matrix, 3) Compute semantic distances between the topics and finally, 4) Calculate a match *score* for each entry. The result is a ranked list of best matching program/content links ordered by this score. For further details of the algorithm please refer to [3].

Metadata and Feature Vector Storage: When new content metadata is imported into the system, each EPG metadataset has to pass through steps 1&2 of the recommendation process. Each entry is then stored in the database along with the computed data as so-called Semantically enriched EPG Dataset (SED). When the user requests a recommendation, only the query-specific input data has to be subjected to aformentioned steps 1&2 for feature computation to be then matched with the stored SEDs to calculate the score.

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[2] **Collaborative filtering** systems base their suggestions on a collection of ratings or usage logs of like-minded *users* and their match with the querying end-user's profile.

[3] **Content-based filtering** extracts information from the *content* via extraction methods (e.g. text mining) or to allocate information about the content from different sources such as the EPG or content categorization metadata.

2.2 Implementation: Centralized and Distributed Architecture

Fig. 1 shows the interface of our *centralized* web-based variant of the recommender service, only requiring an HTML-browser on the client. The four sliders specify the user's mood preference (*fun*, *action*, *thrill* and *erotic*) while the text field accepts allows for alternative verbal input of preferences.

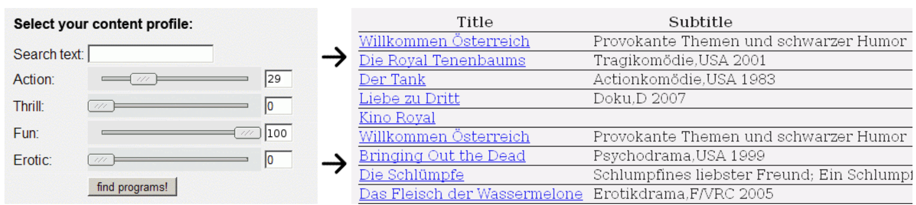

Fig. 1. Query interface (left) set for a preference for 'Fun' and results list (right).

The *distributed* variant of the recommender system particularly targets digital broadcast scenarios with a two-stage processing cycle: Firstly, the SEDs are pre-computed once by the Service Guide Generation Server and then transmitted together with the content stream. Secondly, recommendation generation is executed on behalf of the preprocessed EPG data by a widget locally on the mobile device (e.g. Nokia N800). This way scalability and privacy issues are prevented while limiting device CPU load. The distributed approach has several *advantages*: It only requires a unidirectional broadcast link, avoiding the roundtrip latency of a wireless backchannel. Secondly, the user does not have to perform any registration and profiling steps before using the system. Thirdly, the user's privacy is protected since no personal information leaves the client device.

3 Future Work

Future investigations will address the applicability of our approach to targeted advertising and automatic generation of personal content streams in the context of MBMS (Multimedia Broadcast Multicast Service) and IMS (IP-Multimedia Subsystem). Furthermore, we will evaluate the added value of learning algorithms based on explicit and implicit user feedback e.g. modifying weights by comparing system's suggestions with the content actually chosen by the user.

References

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