

KMulE: A Framework for User-Based Comparison of Recommender Algorithms

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ABSTRACT

Collaborative Filtering Recommender Systems come in a wide variety of variants. In this paper we present a system for visualizing and comparing recommendations provided by different collaborative recommendation algorithms. The system utilizes a set of context-aware, hybrid, and other collaborative filtering solutions in order to generate various recommendations from which its users can pick those corresponding best to their current situation (i.e. context). All user interaction is fed back to the system in order to additionally improve the quality of the recommendations. Additionally, users can explicitly ask the system to treat certain recommenders as more important than others, or disregard them completely if the list of recommended movies is not to their liking.

ACM Classification Keywords

H.3.3 Information Search and Retrieval: Retrieval models;
H.3.5 Online Information Services: Web-based services

General Terms

Algorithms, Design, Experimentation, Human Factors, Performance

Author Keywords

Recommender systems, human factors, evaluation, analysis, personalization, user-centric evaluation, context-awareness, movie recommendation

INTRODUCTION

Recommender Systems (RS) have been a central part of the World Wide Web for as long as it has existed, online RSs actually pre-date the Web itself [2]. One of the most popular recommendation techniques, Collaborative Filtering (CF), analyses users' historical data in order to find items which could be of interest now.

In this paper, we present a system which utilizes several CF techniques to find movie recommendations for users, and presents them on a per-algorithm basis allowing the user to

give feedback on which recommender is preferred at a certain point in time (i.e. in a certain situation). The demonstration shows a movie RS built to evaluate different types of recommendation algorithms providing users with descriptions of why they are being recommended certain movies, allowing the user to implicitly change the context [1] by selecting a different recommender.

CONTEXT-BASED MULTIMEDIA RECOMMENDER

The Context-based Multimedia Recommender System (KMulE) consists of several recommender algorithms developed within the project providing recommendations for a movie recommendation demo website. Users can either register and create persistent profiles for multiple use which allows storing their movie ratings for personalized recommendations, or create profiles offhand by rating a smaller set of movies for instant, personalized recommendations. In addition to their ratings, the systems also keeps track of users' ages, genders, locations (where they live), etc. If users have persistent profiles, additionally data on which recommender algorithms were used at which point in time and what type of recommendation was rated is stored in order to help model the users' contexts.

The system performs recommendations using several types of algorithms including variants of context-aware and hybrid ones, additionally a standard CF baseline recommender is used for comparison. The majority of the implemented algorithms have been described in closer detail in related publications, the context-aware approaches, e.g. interaction-based, event-based, user-based in [4, 5, 8] and combinations of hybrid recommenders, e.g. popularity-based, tag-based in [6, 7]. Additional similar approaches have been presented in [3]. We refer to these publications for detailed information on how the recommender algorithms and approaches work and perform.

RECOMMENDER UI

The user interface used in the KMulE system is a website which presents its users with several options on how to obtain recommendations for interesting movies. First, a user either has to create a persistent user profile, or create a one offhand in order to test the system before registering. However, persistent profiles contain more information, and thus allow for more personalized and accurate recommendations.

Both the offhand user creation page as well as the persistent user creation page asks the users to provide some basic data about themselves (age, gender, location, etc). After filling this out (offhand users), or logging in (persistent users), users

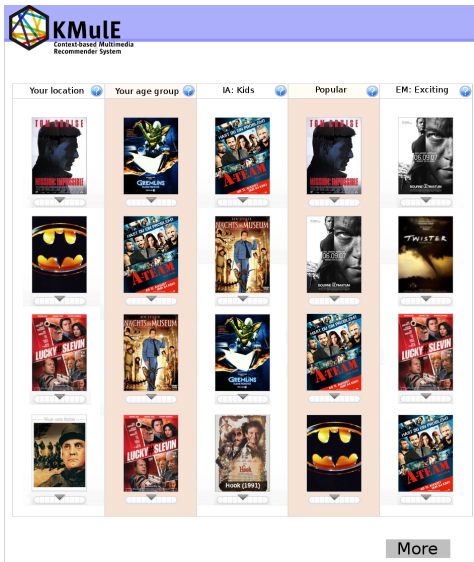


Figure 1. The list of recommendations shown to users. Each column corresponds to one recommender algorithm. Users can choose to rate the movies or the list of recommendations itself.

are met by a page containing movie recommendations. For offhand users, this list contains the most popular movies for different contexts and user profiles (e.g. popular movies in the user's age group). Additionally, there is a search function which the users can use for rating specific movies not presented by the recommenders.

Having rated a set of movies, the recommenders begin to provide personalized recommendations, shown in Figure 1. Each column corresponds to one of the recommenders implemented in the system. Being presented with a set of recommended lists of movies, users can choose to give feedback on the list of recommended movies (as shown in Figure 2) or click a link to show more lists of recommendations by other recommendation algorithms. Users can choose to either not show or increase the importance of recommendations from a certain recommender. In doing so, the system can obtain more knowledge on whether users perceive certain recommenders to be positive or not. Additionally, by rating movies in any of the columns, the system collects information on whether a certain recommender generated a successful recommendation (a rating was performed), or not (no rating performed).

The system which has been presented in this paper allows for a user-based evaluation of specific recommendation algorithms. The feedback obtained from the user can be used directly by the system to provide better recommendations, and give relevant insights into what items and contexts are important at which points in time.

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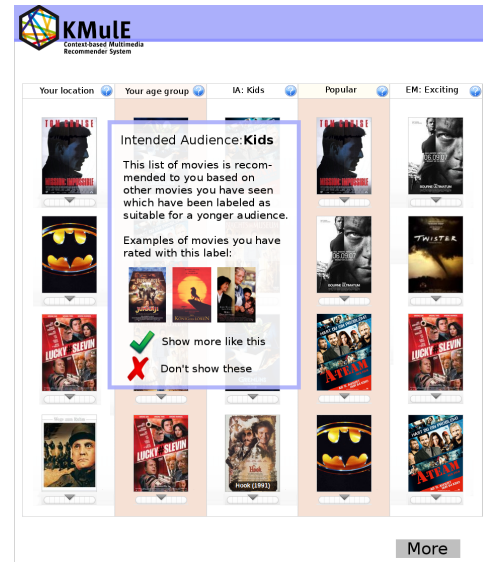


Figure 2. The explanation to why a certain list of recommendations is shown to a user.

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