Predicting Future User Behaviour in Interactive Live TV

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Abstract. Recommender systems are a means of personalisation providing their users with personalised recommendations of items that would possibly suit the users needs. They are used in a broad area of contexts where items are somehow linked to users. The creation of recommendations of interactive live TV suffers from several inherent problems, e.g. the impossibility to foresee the contents of the next items or the reactions of the user to the changing programme.

This paper proposes an algorithm for building personalised streams within interactive live TV. The development of the algorithm comprises a basic model for users and media items. A first preliminary evaluation of the alogithm is executed and the results discussed.

Keywords: recommender system, interactive live TV, multistream.

1 Introduction and Related Work

Recommender systems are a means of personalisation providing their users with personalised recommendations of items that would possibly suit the users needs. They are used in a broad area of contexts where items are somehow linked to users. Recommender systems are used in a great variety of contexts (e.g. [1], [2]). last.fm [3] and Lifetrak [4] bring recommender system research to continuous media consumption.

This paper proposes an algorithm for building personalised streams within interactive live TV. The development of the algorithm comprises a basic model for users and media items. Additionally, means are introduced to overcome the problems inherent in the character of live TV.

Recommender systems have been strongly researched in the last time (cf. [5], [6]). In [7] and [8] it has been shown that hybrid recommender systems perform better than either content-based or collaborative filtering algorithms. Tagging, a new flexible means to classify items, allows categorisation of items with loosely associated keywords. This can be used in order to provide descriptions for content-based filtering [9], [10]. It can also help to overcome the vocabulary problem (cf. [11]).

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2 Requirements for Recommender Systems in the Context of Live-Transmissions

We are considering here interactive TV in the context of live transmissions, which are aimed at mass events like the Olympic Games. There several things happen at the same time, and generally broadcasters are provided with a multitude of parallel audio visual feeds from a central broadcasting company. Instead of creating only one interactive TV stream, these streams will be used to broadcast several interactive TV streams live in parallel. This is already planned in the research project LIVE [12] and will be tested during the Olympic Games in Beijing 2008. The iTV show is to customise itself to the viewer. The aim is to prevent a mere "zapping" behaviour of the consumer at home. This will be accomplished by interlinking the parallel live streams to guide the consumer and enhance the streams with archive material to ensure a dramaturgical integrated user experience.

The requirements of a recommender system in live iTV differ significantly from those of a non-live environment. Implementing a personalised EPG does not suffice. In contrast, rating the programme and recommending a new programme item must be an ongoing process. A recommendation system for live iTV can provide different user experiences to the viewer: In a rather passive lean-back approach it would liberate the user from having to decide consciously which programme to watch, a lean-forward approach would require the user to decide whether to follow a recommendation or not.

Recommender systems supporting live broadcasts have to face some key problems due to the nature of live events. Content-based filtering suffers from the impossibility of providing appropriate content descriptions. As you cannot precisely predict what will happen in the audio visual media streams on the short or long term, you can only provide raw descriptions afore. Furthermore, these descriptions must be associated in real time. Collaborative filtering relies on a critical mass of viewers that must be available. It is impossible to take all registered viewers as a basis, but only consumers currently watching the programme. Hence, you have to induce an action from imperfect data.

3 Development of the Recommender System

As a base for its predictions, our recommender system uses the content-boosted collaborative filtering algorithm developed in [7].

A crucial aspect for calculating recommendations is the accurate description of the user and his relations to the media items. The user profiles are built using two means of user feedback: watching statistics (watching and zapping) and asset rating (favour and dismiss). Both means are bijectively mapped to a benchmark variable as shown in Figure 1. Each media item is tagged with a finite number of tags, where the number of tags may vary between the media items. The rating of a media item is mapped on the asset's tags, i.e. the tags are rated with the same value as the whole asset. The user profile $U_{u,t}$ for user u and tag t is calculated

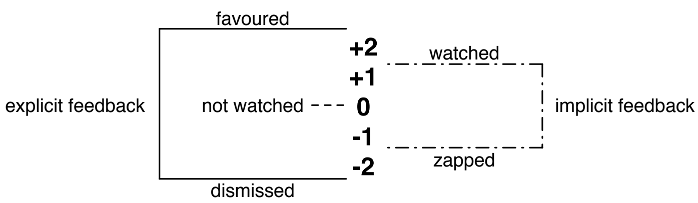

Fig. 1. Values of the benchmark variable used to describe watching and rating of live media assets

as arithmetic mean of the ratings user u gave to items associated with tag t. If u did not rate any item tagged with t, $U_{u,t}$ would have the value of 0.

A content-based prediction for one viewer and one item is calculated as arithmetic mean of the vector containing the mean ratings the viewer gave to the tags associated with that media item. The content-based predictions are calculated according to the profile that has been built up at this time. They serve as a basis for the pseudo user ratings. Figure 2 illustrates the construction of the pseudo user ratings for one example viewer. Each row denotes a live media stream which is divided into a continuous sequence of media assets with some fixed duration.

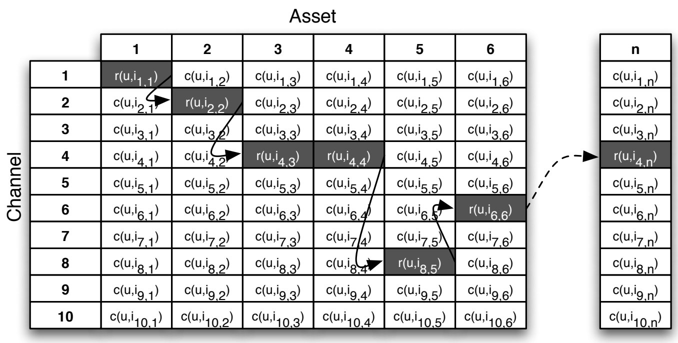

Fig. 2. Construction of the pseudo user ratings for user u. The black background indicates the assets watched by u.

Collaborative filtering for a hybrid recommender is implemented as in [7], where we have omitted any reliability components of the predictors. However, they are planned to be implemented after a field trial in Mid 2008.

In a live broadcasting context, it is impossible to predict the contents of the items that are to be broadcast and the behaviour of the neighbours, i.e. how the neighbours react to that items, in the future. As a replacement, it is assumed that the contents of two sequential items do not differ significantly. Hence for practical reasons, the next item is described in our approach with the description of its preceding item.

4 Evaluation of the Proposed Algorithm

The algorithm is evaluated with the help of a small test application and data derived from watching the interactive DVD "Vision Europe" produced in the EU IST Project MECiTV [13].

Vision Europe provides ten different parallel channels with several predefined switching points. At each switching point, another channel is recommended to the user. In the test case, a media item is defined as 10 second part of the live stream. The test case is rather far away from the real usage scenario because of these editorial switching points.

The algorithm is evaluated through two different metrics: the statistical accuracy metric mean absolute error (MAE) and the decision support measure Receiver Operating Characteristics (ROC). Both metrics compare the actual rating a user gave to an item with the predictions made by an algorithm [7].

The tests have been conducted in October 2007 with 13 employees of Pixelpark Agentur Köln (10 masculine, 3 feminine). As a consequence of the rather small amount of test persons and the not optimal interactive video, the data gathered within the test cannot be classified as good.

Although this is not a representative study, first results can be stated. Both metrics induce that the Content-Based predictor performs better than the hybrid predictor. This might be caused in the bad base data, but the Content-Based predictor already performs quite well with this bad data. The worse performance of the hybrid predictor could be caused by the small number of test persons.

5 Conclusion

The simple but powerful model of the complex system for live recommendations used in the algorithm seemed to suit the requirements of interactive live television. It leads to high quality recommendations for the consumer based on low quality data. It can serve as a basis for further research in live recommender systems. The algorithm will be re-evaluated during a field trial scheduled within the LIVE project [12] during the Beijing 2008 Olympic Games.

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The LIVE project ('Live Staging of Media Events' [12]) is an integrated, multidisciplinary initiative that will contribute to the IST strategic objective 'Semantic-based Knowledge and Content Systems' and 'Exploring and bringing to maturity the intelligent content.

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