Multimedia Broadcasting | Mobacas | Recommendation

Technology Reports

New Service Merging Communications and Broadcasting—NOTTV—

Recommendation Technology for Promoting Use of NOTTV

In Japan, the launch of the NOTTV[*1] *broadcasting station for smartphones in April 2012 marked the start of a new service merging communications and broadcasting. NOTTV features a function for recommending content based on user-viewing habits and terminal-operation history to promote the use of this service. To support this function, NTT DOCOMO has developed a recommendation system that uses communication means to send and receive information between the system and the terminal to provide information and functions such as recommended content, automatic content reservation and content rankings. This system has made it possible to provide each and every user with a service based on individual preferences, which has helped to promote the use of NOTTV.*

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1. Introduction

NOTTV broadcasts a wide array of content covering many genres for either Real-Time (RT)[*2] or Shift-Time (ST)[*3] viewing. However, with so much content available, there are concerns that content selection based only on searches instigated by the user will expose the user to only a limited amount of content resulting in lost content-viewing opportunities. To address this issue at NTT DOCOMO, we have developed a high-performance recommendation system for NOTTV. This system is deployed through the use of bidirectional communications on the Mobacas™[*4] multimedia broadcasting service.

By introducing a recommendation system, we can bring interesting content to the user's attention, which we see as promoting the use of NOTTV and increasing content-viewing opportunities. In this system, the terminal acquires a list of recommendations output by the system and guides the user to content viewing by displaying this list as recommended content on the screen as shown in **Figure 1** and by making content available for automatic downloading and storage.

In this article, we discuss the issues that had to be resolved in achieving this system, describe the individual technologies and functions making up the

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*1 **NOTTV™**: NOTTV and the NOTTV logo are trademarks or registered trademarks of mmbi, Inc.

*2 **RT**: Real-time viewing of a program delivered by broadcast signals the same as existing TV.

*This is provided only in Japanese at present.

Figure 1 Recommended content display

system, and present the system configuration.

2. Issues in Developing a Recommendation System

The following features of the NOTTV service must be taken into account from the viewpoint of a recommendation system:

- A wide variety of content formats exist.
- The provision of content via broadcast signals promotes frequent switching of content.
- No operation history is stored for new users.

These features give rise to the following three issues in the development of a recommendation system:

- What recommendation algorithms should be adopted for NOTTV?

Given the huge volume of available content, it is important to recommend with good accuracy those items of content that can attract the user's interest. In this regard, conventional recommendation technologies [1][2] are faced with the "cold start" problem in which recommendable content is limited right after launching a service due to the small amount of user operation history. It is therefore essential that recommendation algorithms that can solve this problem be adopted for NOTTV.

- How can flexible recommendation operations be achieved?

It must be possible to set a variety of recommendation rules and parameters with respect to the many and varied content formats in NOTTV. There is also a need for an operation environment in which the effectiveness of previously applied recommendation settings can be quantitatively measured and settings can be fine-tuned on the basis of those measurements to improve the system.

- How can high-speed data processing technology be deployed?

Since content targeted for calculations is frequently changing in this service, it is imperative that recommendations be updated quickly.

3. Technologies Implemented in the Recommendation System

3.1 Recommendation Algorithms

We here describe the features of content-based filtering and hybrid collaborative filtering as algorithms implemented in the recommendation system for NOTTV. Content-based filtering drives the selection of content that matches the preferences of an individual user while hybrid collaborative filtering broadens the range of recommended content.

1) Content-based Filtering

In this system, content-based filtering incorporates both a user-information-based recommendation method and an item-based recommendation method.

The user-information-based method generates recommendations based on

*3 **ST**: Viewing when desired by the user of content reserved beforehand and automatically stored on a Mobacas terminal. On NOTTV, an item delivered for RT is called a "program" while an item delivered for ST is called "content," but in this article, all viewable items are uniformly called "content."

*4 **Mobacas™**: Mobacas and the Mobacas logo are trademarks of Japan Mobilecasting, Inc.

content features and user preferences. This method expresses content or user preferences in the form of a feature vector*5 as shown in **Figure 2** [3]. The content feature vector is computed from the frequency of appearance of specific words in metadata, while the user feature vector expresses user preferences based on the operation history of that user [4]. The vector similarity*6 between each user's feature vector and content feature vectors can be calculated to recommend content that matches the preferences of each user.

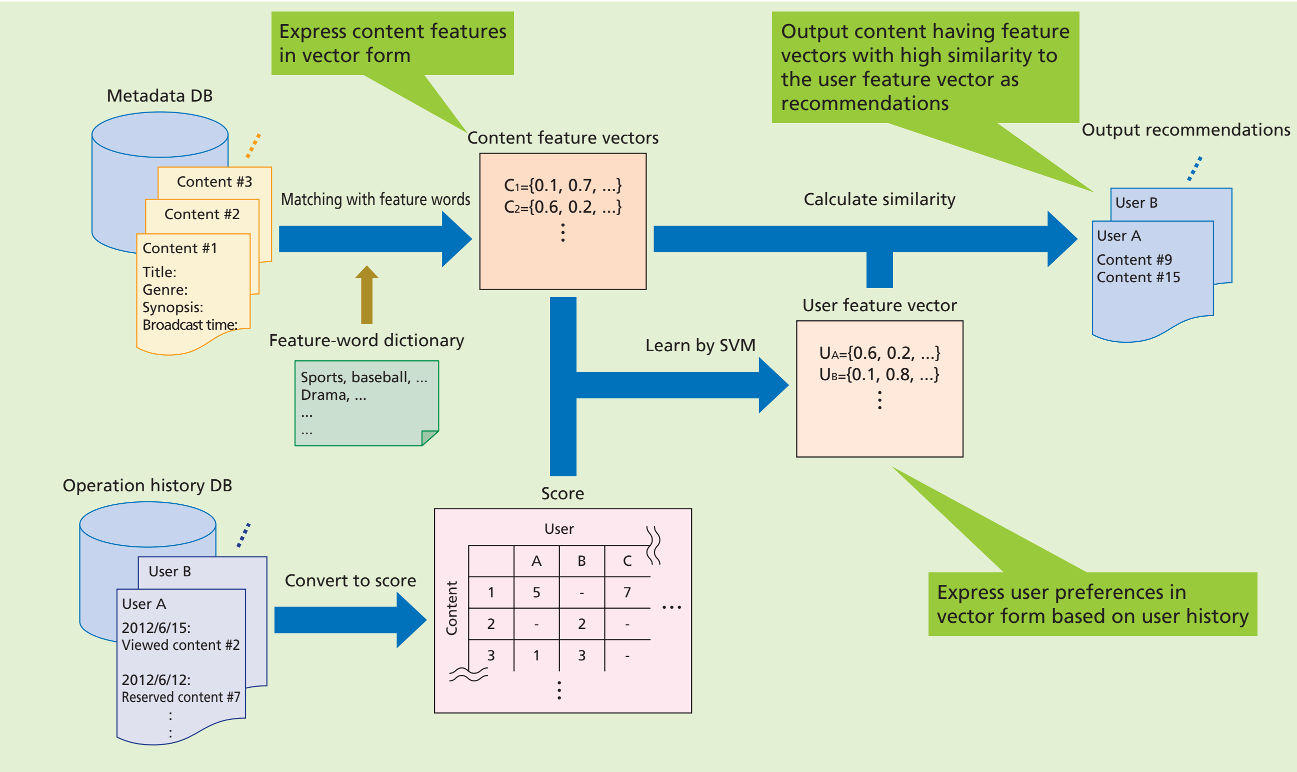
Next, we describe the item-based recommendation method. This algorithm selects content having a high degree of similarity with certain content. Specifically, it calculates the similarity between the feature vector of a certain item of content with that of other items of content and recommends those items having high similarity as related content.

Content related to a specific item of content presently being displayed on a terminal can be presented to the user as a means of bringing other content to the user's attention and providing access to it.

2) Hybrid Collaborative Filtering

This type of filtering generates recommendations for a user based on content feature vectors and on user feature vectors of other users having similar preferences.

For each user, this algorithm first generates a new user feature vector from the user feature vector of the target user and the feature vectors of other users having a high similarity with that user [5]. In other words, it obtains a user feature vector that incorporates the features of other users whose preferences are close to that of the target user. The algorithm then calculates the similarity between this new user feature vector and content feature vectors and uses that similarity to determine which



Score: A measure indicating the degree of interest that a user has with respect to an item of content. The score rises with viewing or reserving actions.
Support Vector Machine (SVM): A pattern-recognition technique used in this recommendation system to learn user preferences and calculate the user feature vector.

Figure 2 Generation of recommendations based on user preferences

*5 **Feature vector**: A means of quantifying the frequency of appearance of feature words in vector form.

*6 **Vector similarity**: A measure of similarity between a certain vector and some other vector. A larger value indicates a greater degree of similarity.

content to recommend.

In contrast to conventional techniques that simply recommend content viewed by similar users, this technique decides the content to recommend after updating the user feature vector. This means that even content that has yet to be viewed by any user can still be targeted for recommendation thereby solving the cold-start problem.

3.2 Recommendation Operations

The fine-tuning of service settings is important in a recommendation system. To obtain a positive effect, appropriate settings must be determined by repeating a "hypothesize, set, evaluate and improve" cycle. This process begins by making a hypothesis as to what kind of recommendations might be effective, making actual settings and providing recommendations. It then evaluates the effect of those settings and makes improvements by modifying the settings as needed. Our recommendation system for NOTTV supports the above cycle via an operator's screen. The concept of performing recommendation operations using this screen is shown in **Figure 3**.

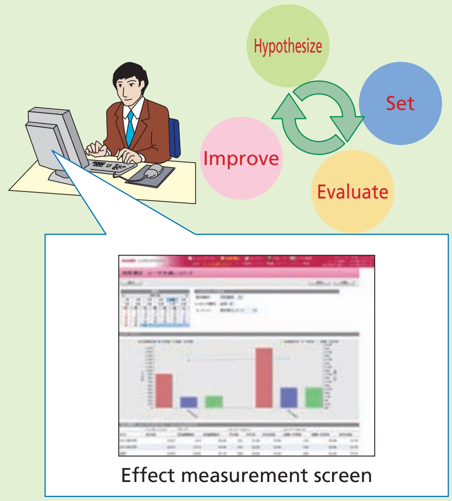


Figure 3 Recommendation operations

1) Recommendation Settings

This recommendation system features an operation environment that enables an operator to create, delete and edit recommendation types, which serve as units for providing recommendations to users. The operator can set a recommendation type so created in combination with any of the algorithms described above and rules of the operator's choosing. Recommendation rules can be used to add, delete or sort content based on metadata such as content genre and title and on user attributes and operation history. The operator can also check and edit a created recommendation list in real time. This editing can be performed in units of content items such as by adding specific items of content or changing the sort order. A recommendation list can also be controlled through a manual delivery process that allows the list to be delivered only after being checked by the operator and an automatic delivery process in which no pre-checking is required.

This recommendation system also enables the operator to make updates and changes to the feature-word dictionary, recommendation algorithms, and recommendation-engine internal processing parameters without having to halt the service. As a result, parameters specified in the "set" step in the above operations cycle can be reflected immediately in the recommendation engine and used in all subsequent recommendation-generation processing.

2) Effect Measurement

In this recommendation system for NOTTV, the effect of recommendations can be quantitatively evaluated using impression[*7], click-through[*8] and conversion[*9] indices. These indices are calculated on the basis of user operation history collected from the terminal. They can be displayed on the operator's screen in graph or table form for any period in hour, day or month units. The operator is therefore able to obtain a quantitative and visual understanding of the extent to which recommendations

*7 **Impression**: An index indicating the number of times that recommended content has been displayed.

*8 **Click-through**: An index indicating the number of times that the user has reviewed detailed information on recommended content.

*9 **Conversion**: An index indicating the number of times that the user has reserved or viewed recommended content.

are creating opportunities for user viewing. The operator can also divide users into groups and make different recommendation settings so that "A/B testing" can be performed to determine which group setting was the most effective over the same time period. Effect measurement can be performed online and the effect of recommendations can be checked during the daily operation of the recommendation service. At this time, settings can be assessed in the "evaluate" step and made optimal in the "improve" step of the operations cycle.

3.3 Distributed Processing Technology (Hadoop)

NOTTV requires a huge volume of data processing related to operation history, metadata, etc. In conventional DB-centered processing methods, an increase in the amount of data to be processed results in a dramatic increase in DB access load and processing time. This recommendation system adopts the Hadoop™*10 [6] platform for parallel distributed processing to speed up recommendation calculations. Hadoop enables different resources to be allocated to different users for tasks like feature vector generation and similarity calculation thereby achieving parallel distributed processing.

In the above way, we have achieved high-speed recommendation processing to enable the provision of up-to-date recommendations for users.

4. System Configuration

The configuration of the recommendation system is shown in **Figure 4**.

The internal part of the system consists of a front-end server for performing online processing such as managing system access from user/operator terminals and customer authentication, a DB server for managing operation history, metadata*11, and the recommendation list, and a batch server and Hadoop [6] server for performing recommendation computational processing.

Interfaces to the external part of the system connect to user terminals and the operator's screen, to the customer management system that manages customer attributes and contract status, and

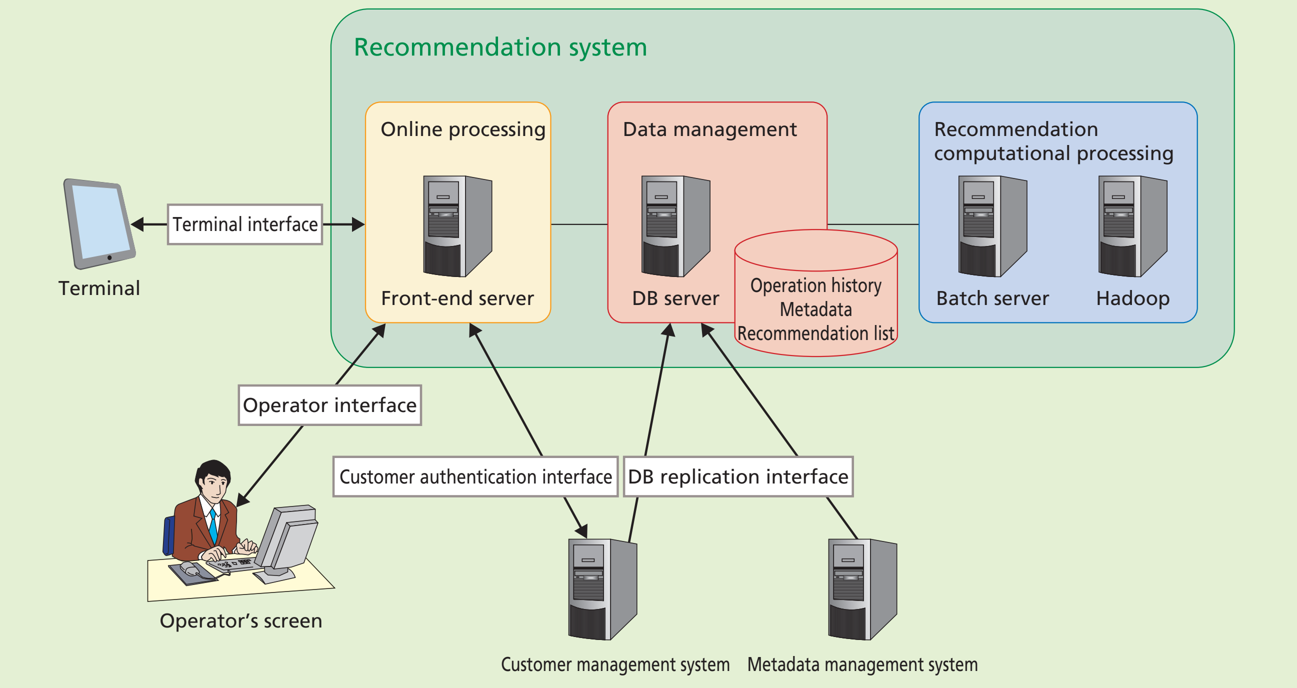


Figure 4 Configuration of recommendation system

*10 **Hadoop™**: A platform for achieving parallel distributed processing. Hadoop is a registered trademark of Apache Software Foundation.

*11 **Metadata**: Data providing a synopsis, describing the genre, etc. of content.

to the metadata management system that manages content information. The user-terminal interface, in addition to functions for sending/receiving recommendation lists and user operation history, includes a function for obtaining a list of content based on keywords registered by the user and a function for resetting information on user preferences stored on the system.

As for the operator interface, we developed an operator's screen as described above and an Application Program Interface (API)*12. We also equipped the customer management system and metadata management system with a function for providing the recommendation system with customer information and metadata through DB replication*13.

5. Conclusion

In this article, we described a recommendation system for NOTTV. This system promotes the use of NOTTV by incorporating recommendation algorithms based on user preferences and providing flexible operation functions and high-speed recommendation processing. Looking forward, we plan to make improvements to this system using feedback obtained from actual service operation.

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*12 **API**: An interface enabling the functions provided by a recommendation system to be used by other systems, terminals, etc.

*13 **DB replication**: Technology for copying the content of a certain DB to other DBs.