Automatic tracking and control for web recommendation

New approaches for web recommendation

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***Abstract*— In this paper, we assume that users and their consumptions of television programs are vectors in the multidimensional space of the categories of the resources. Knowing this space, we propose an algorithm based on a Kalman filter to track the user's profile and to foresee the best prediction of their future position in the recommendation space. The approach is tested on data coming from TV consumptions. Using these results, we derive a new strategy for web recommendation based on a control loop. To conclude, we propose a new users' monitoring approach.**

Keywords-recommender system; user profile; target tracking; Kalman filter; control loop

I. INTRODUCTION

In Web-based services of dynamic content, recommender systems face the difficulty of identifying new pertinent items and providing pertinent and personalized recommendations for users.

Personalized recommendation has become a mandatory feature of Web sites to improve customer satisfaction and customer retention. Recommendation involves a process of gathering information about site visitors, managing the content assets, analyzing current and past user interactive behavior, and, based on the analysis, delivering the right content to each visitor.

Recommendation methods can be distinguished into two main approaches: content based filtering [9] and collaborative filtering [10]. Collaborative filtering (CF) is one of the most successful and widely used technology to design recommender systems. CF analyzes users' ratings to recognize similarities between users on the basis of their past ratings, and then generates new recommendations based on like-minded users' preferences. This approach suffers from several drawbacks, such as cold start, latency, sparsity [11], even if it gives interesting results. Furthermore, this approach does not consider the dynamical aspect of web browsing, i.e., going from page to page (or web resources) as we can move from place to place.

This is the reason why the main idea of this paper is to propose an alternative way for recommender systems based on the following assumption: we consider Users as target moving along a trajectory in the recommender space. This dynamic system can be modeled by techniques coming from control system methods and we use Kalman filtering to predict future positions of the users in the recommender space, i.e., the expectable movies categories to be seen. We will detail the backgrounds of this approach. Then, we expose the recommendation strategies. In our conclusion, we will give some guidelines for future works.

II. PRINCIPLES

Kalman filter is an optimal state estimator of a linear system. It can estimate the state of the system using a priori knowledge of the evolution of the state and the measurements. Kalman filter has main applications in control systems and in target tracking.

A. *Target tracking in the cyberspace*

Our hypothesis: the user is a target which is moving along an a priori unknown trajectory in the multidimensional space of the categories. Figure 1 shows the principle of our approach.

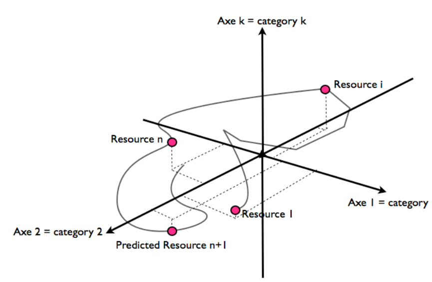

Figure 1. Trajectory in the recommender space

By measuring the successive positions of the users in the space (the seen movements), we can model a trajectory and by using a state space cinematic model, we can predict future positions in the space.

B. *Kalman filter: equations*

How can we know about a target moving in the recommender space?

We choose to represent a state vector containing three components: one for the position, one for the speed and one for the acceleration. The state vector has the following form:

$$X_k = \begin{bmatrix} x \\ \dot{x} \\ \ddot{x} \end{bmatrix}_k \tag{1}$$

where:

x is the vector containing the position vector (the position is given by the Quantity of Interest given related to the different categories see Part IV)

$\dot{x}$ is the vector containing the speed vector

$\ddot{x}$ is the vector containing the acceleration vector.

$\dot{x}$ and $\ddot{x}$ are introduced in the state vector to take into account the dynamic variations in the positions of the target.

The dynamic of this state vector will be modeled by a state space model which has the following form:

$$\begin{cases} X_{k+1} = AX_k + w_k & \text{(2.a)} \\ Z_k = HX_k + v_k & \text{(2.b)} \end{cases}$$

where matrix A includes the relationship between the position, speed and acceleration where T represents the time period. In our case, we consider T = 1. w_k and v_k are random noises which take into account unexpected variations in the trajectories.

$$A = \begin{bmatrix} \alpha & T & \frac{1}{2}T^2 \\ 0 & \alpha & T \\ 0 & 0 & \alpha \end{bmatrix} \tag{3}$$

Matrix H, called the measurement matrix, is structured to obtain in equation (2.b) the values of the positions in the recommender space. Thus, H will have the following structure as shown in the figure 2.

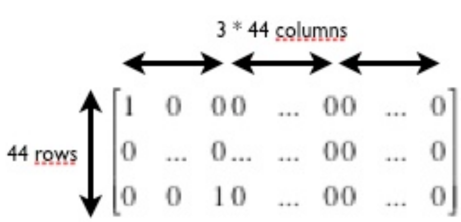

Figure 2. Structure of Matrix H

The Kalman filter equations are then given by the following equations [6]:

Prediction: it is the predicted state knowing past values

$$\begin{cases} \hat{X}_{k+1/k} = \hat{X}_{k/k-1} + K_k\left(Z_k - H\hat{X}_{k/k-1}\right) \\ \qquad = \left(A - K_kC\right)\hat{X}_{k/k-1} + K_kZ_k \end{cases} \tag{4}$$

Kalman gain: it described the dynamic of the filter. The dynamic takes into account the variations of the moving target.

$$K_k = AP_{k/k-1}H^T\left(HP_{k/k-1}H^T + R\right)^{-1} \tag{5}$$

The evolution of the uncertainty on the estimation is then given by:

$$P_{k+1/k} = AP_{k/k-\&}A^T - AP_{k/k-1}H^T\left(HP_{k/k-1}H^T + R\right)^{-1}HP_{k/k-1}A^T \tag{6}$$

where the initial conditions (which initialize the filter) are given by:

$$\hat{X}_{0/-1} = X_0 \, , P_{0/-1} = P_0$$

and the state prediction by:

$$\hat{X}_{k+1/k}$$

The principle of the filter is described by the following figure:

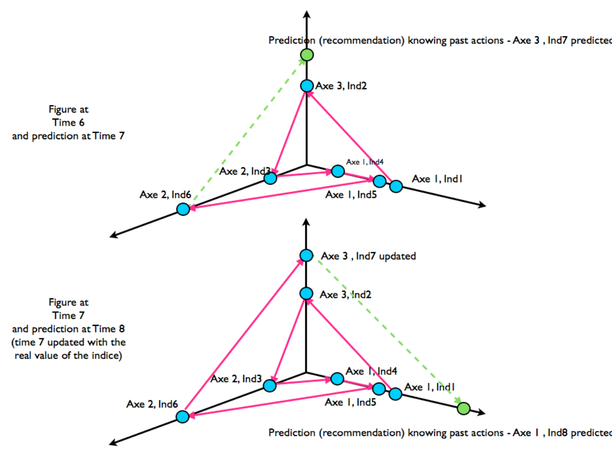

Figure 3. Principle of the position prediction

We apply these equations on an experiment based on TV consumptions.

III. FIRST EXPERIMENT

A. *Description of the experiment*

The dataset is the TV consumption of 6423 English households over a period of 6 months (from 1st September 2008 to 1st March 2009) (Broadcaster Audience Research Board, [7]), [8]. This dataset contains information about the user, the household and about television program. Each TV program is labeled by one or several genres. In the experiment, a user profile build for each person. The user profile is the set of genres associated to the value of interest of the user for each genre. This user profile is elaborated in

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function of the quality of a user's TV consumption: if a TV program is watched entirely, the genre associated to this TV program increases in the user profile. Several logical rules are applied to estimate the interest of a user for a TV program.

The methodology of the experimentation is the following:

- The Kalman filter is applied iteratively to estimate the future positions of the user in the space.

The entire consumption is described by 44 categories, which will define the 44 dimensions of the recommender space where users are "moving".

B. Numerical results

The obtained results can be exposed as follows:

Kalman filter predicts the interest of a specific user for a subset of genders knowing his past. Using this prediction, we can propose a new recommendation strategy:

- If the Quantity of Interest (QoI) of the user is predicted to be in one specific region of the space, we can recommend something inside this specific region:
  - For example, if the specific region is defined by dimensions Documentary and Drama, we can recommend contents related to these two dimensions
- If the predicted quantity of interest (QoI) changes to another dimension of the space, we can automatically recommend content from this new region of the space.

C. Results

The results can be analyzed as follows: Kalman filter predicts the specific interest for a category of contents of one user.

Figures 4 and 5 show Estimation / Prediction computed by Kalman filtering. Doted-lines show the evolution of the real values. Continuous lines show the obtained predictions.

In Figures 4 and 5, we can see the estimation/prediction given by the Kalman filter: green lines show the prediction obtained at each time using the knowledge we have of the degree of interest of each user. We can see that the prediction fits the real values even if they present abrupt variations.

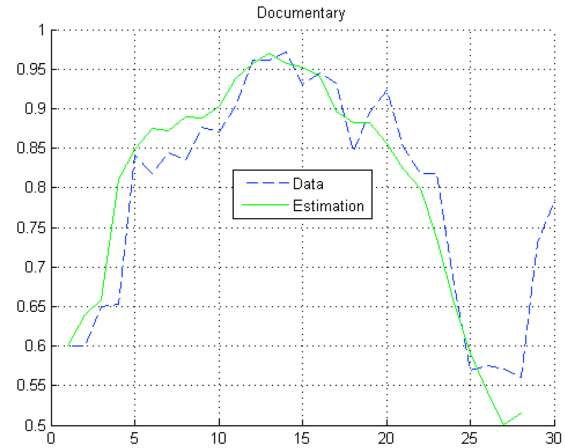

Figure 4. Prediction for Drama

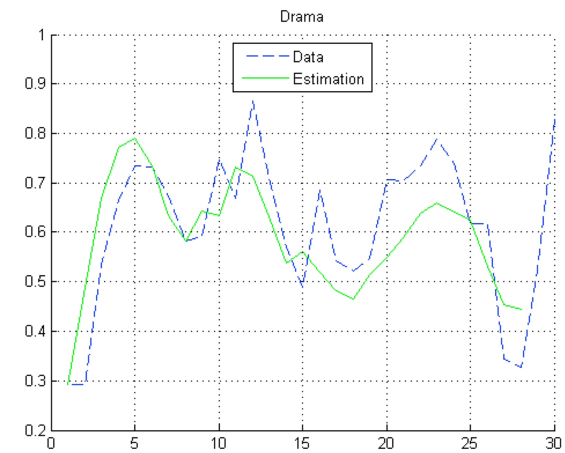

Figure 5. Prediction for Documentary

IV. RECOMMENDATION STRATEGY

In this approach, we can build a recommendation by analyzing the estimation provided by Kalman filter.

The profile is built from the consumption of TV programs. Each TV program is defined by concepts such as entertainment, science fiction, talk show, etc. The analysis of the way different TV programs are watched allows deducing the interest of a user for each concept.

Our new recommending strategy is based on control loop which can be described by Figure 6.

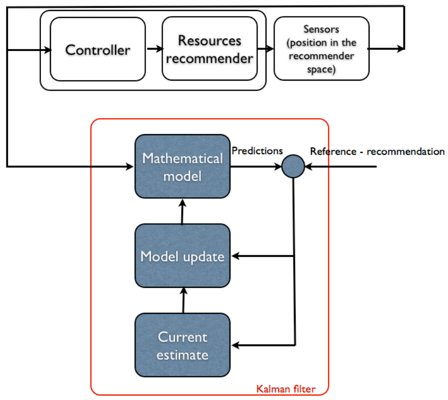

Figure 6. Control loop for recommendation

This control loop will observe the difference between the estimated concept and the calculated concept and it will integrate the controller/recommender the following strategy:

- If the computed concept is superior to the estimated concept (noted negative difference), then the user's interest for this concept is decreasing.
- If the estimated concept is superior to the computed concept (noted positive difference), then the user's interest for this concept is increasing.

The process will focus on the concepts showing up a big difference: the concepts with an important positive difference influence the recommendation towards these concepts, whereas the concepts with an important negative difference discourage the recommendation towards these concepts.

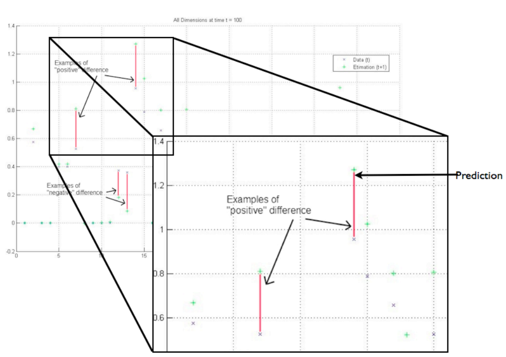

Figure 7. Analysis of the evolution of the prediction for recommendation

Conversely to existing methods which recommend precise contents for a given user, this method will performs on the macroscopic level, i.e., subspaces of specific categories. The strategy will isolate the appropriate subspace and the recommendation will be done in the related categories. Then, we can imagine to have a more precise recommendation by computing a second iteration (target tracking in the trajectory in the subspace and positions prediction) on the subspace (zoom effect).

To summarize, the recommendation is based on the two preceding arguments.

- the user's actual state of mind
- the subset of retained dimensions.

From these “positive” or “negative” dimensions and from the TV program, we have to define the recommendation for a set of TV programs for that day. Furthermore, according to what the user watched during the day, we can refine our recommendation. Indeed, in our example, if the user is interested in contents of types x, y and z and if he has already watched content of type x and y that day, the recommendation would essentially concentrate on content of type z.

Hence, we will need to make a last step which will be devoted to the identification of the appropriate content which corresponds to the estimation of the dimensions' evolution.

V. Conclusion

Our original approach considering users as target moving along trajectories in subspaces of the recommendation space will solve web recommendation as a control system problem. Web recommendation becomes a system described by a state space model to be controlled or tracked. By comparing inputs to predicted and/estimated values, we obtain a new kind of recommender systems which will consider as moving targets to be identified or dynamic systems to be controlled.

Then, in our case, knowing the past positions of the user in this space along the different axis of the 44 dimensions space, our Kalman filter based recommender system will suggest:

- if the user is interested in contents of types x, y and z and if he has already watched content of type x and y, the recommendation would essentially concentrate on content of type z.

At last, the strength of our approach is in its capability to make recommendations at a “higher level”, which fit users habits, i.e., given main directions to follow knowing the trajectory in the space and not to suggest specific resources. Furthermore, the trajectories in the recommender space give the opportunity to compute a monitoring system where we can visualize in real time the users’ trajectories (see Figure 8).

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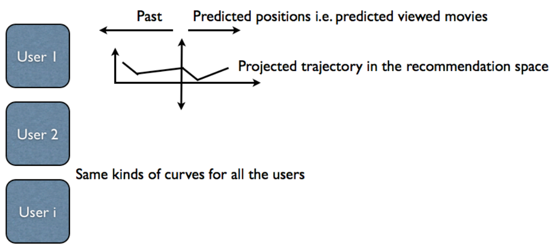

Figure 8. Users monitoring

Future works will be focused on tracking groups of users and on the definition of the topology of the recommendation space as a space including specific mathematical operators.

References

[1] Anderson, B. and Moore, J. B., 1977. Optimal filtering. Prentice Hall – Information and System Sciences Series

[2] Gibson, W, 1988. Neuromancien. Collection J'ai Lu, La découverte, ISBN 2-7071-1562-2

[3] Söderström, T., 1994. Discrete-time stochastic systems: estimation and control. Prentice Hall International.

[4] Box, G.E.P. and Jenkins, G.M., 1970. Time series analysis: forecasting and control. Holden Day.

[5] Bernier C., Brun A., Aghasaryan A., Bouzid M., Picault J., Senot C., and Boyer A., 2010. Topology of communities for the collaborative recommendations to groups, SIIE 2010 conference, (Sousse, Tunisia, February 17 – 19, 2010).

[6] Gevers, M. and Vandendorpe, L. Processus stochastiques, estimation et prediction. DOI=http://www.tele.ucl.ac.be/EDU/INMA2731/].

[7] BARB: Broadcaster Audience Research Board, DOI=http://www.barb.co.uk/.

[8] Senot, C., Kostadinov D., Bouzid M., Picault J., Aghasaryan A., and Bernier C., Analysis of strategies for building group profiles. User Modeling, Adaptation and Personalization. Lecture Notes in Computer Science, 2010, Volume 6075/2010, pp. 40-51

[9] Pazzani M. and Billsus D., 2007. Content-Based Recommendation Systems. In Brusilovsky, P. Kobsa, A. Nejdl, W. (réds) The Adaptive Web: Methods and Strategies of Web Personalization, pp. 325–341.

[10] Goldberg D., D. Nichols, B. Oki, and D. Terry, 1992. Using Collaborative Filtering to Weave an Information Tapestry. Communications of the ACM, 35(12), pp. 61–70

[11] Grcar M., Mladenic D., Fortuna B., and Groblenik M., 2006. Data Sparsity Issues in the Collaborative Filtering Framework. Advances in Web Mining and Web Usage Analysis, pages 58–76

[12] Smith, J., 1998. The book, The publishing company. London, 2nd edition