Reports Recommendation in Wiki-news system based on AIS methods

Janusz Sobecki and Leszek Szczepański
Wroclaw University of Technology
Wyb. Wyspianskiego 27, 50-370 Wroclaw Poland
Phone: +48-320-3195, Fax: +48-320-3453
email:sobecki@pwr.wroc.pl

ABSTRACT: Recommender systems are applied in many areas such as information retrieval, web browsing or information filtering. They are applying many different reasoning methods that are known from many disciplines such as Artificial Intelligence, Expert Systems or Information Retrieval. Recently, the recommender systems also adopt some nature inspired methods such as Artificial Immune System (AIS). In this paper we present application of AIS collaborative filtering in Wiki-news articles recommendation. Wiki-based information systems are gaining its popularity among many different users so it is becoming necessary to apply recommendation for most effective information delivery.

KEYWORDS: Artificial Immune System, Wiki-based System, Recommender System, Wiki-news

INTRODUCTION

Recommender systems are nowadays applied in many areas and are gaining popularity among internet systems providers because of to their ability to deliver customized information for their users. The main application areas are following: e-commerce, web content, web advertising and also user interfaces.
Recommender systems are applying many different reasoning methods that are known from many disciplines such as Artificial Intelligence, Expert Systems or Information Retrieval. Recently, the recommender systems also adopt some nature inspired methods such as Artificial Immune System (AIS). In the Biology, the immune system is defined as "the system of specialized cells and organs that protect an organism from outside biological influences" [10]. In the literature we can find some application of AIS for collaborative filtering. In this paper we present application of AIS collaborative filtering in wiki-news articles recommendation. Wiki-based information systems are gaining its popularity among many different users so it is becoming necessary to apply recommendation for most effective information delivery.
AIS is used to select the group of other system users with similar preferences. In AIS that is kind of simulation of Human Immune System where the antigens attacking our body can stimulate the immune system to produce antibodies [9]. Using AIS nomenclature for our recommender system, wiki-news is a *body*, any new user is an *antigen* and similar users are called *antibodies* that protect the body. In our system we used weighted kappa affinity measure algorithm to calculate the correlation coefficients. Having correlations between all antibodies we can eliminate antibodies if correlation is lower than the suitable weighted kappa value. If antibodies concentration is high enough, then we can make predictions about wiki-news article relevance for any new user. The quality of recommendation was verified experimentally using two measures precision and accuracy of recommendation and proves to increase when correlation increases.
Besides article recommendation we also verified how antibodies correlation based on the information content preferences may have an influence on the interface layout preferences, in this case however the accuracy of layout recommendation is more independent from the correlation coefficients.
The paper contains general information on recommendation methods in the section Recommendation Systems. The following section presents basic information on Artificial Immune Systems (AIS) application in recommender systems. Then the general architecture of the Wiki-news system is described. The implementation and experimental results are presented in the following section. The paper conclusions are given in the Summary.

RECOMMENDER SYSTEMS

The growing popularity of different web-based systems recommendation methods help to deliver customized information to a great variety of users and may be applied in many different domains, such as [6]: net-news filtering, web recommender, personalized newspaper, sharing news, movie recommender, document recommender, information recommender, E-commerce, purchase, travel and store recommender, E-mail filtering, music recommender and music list recommender.

The central problem of all the recommender systems is user modeling [5]. The user model concerns usually data: content, representation and utilization within the systems. The data is divided into two main parts: user data that characterizes the user itself and usage data. The former contains information on demographic data, users' knowledge, their skills and capabilities, their interests and preferences and also their plans and goals; and the later concerns different selective operations that express users' interests, unfamiliarity or preferences, temporal viewing behavior, as well as ratings concerning the relevance of these elements.

The problems of the user modeling concerns the following elements[6]: user profile generation, initial profile generation, profile learning technique, relevance feedback, information filtering method, user profile-item matching technique, user profile matching technique and profile adaptation technique. One of the most distinguishing dimensions of the recommender systems is information filtering method that according to [6] may be: demographic (DF), collaborative (CF), content-based (CBF) and hybrid (HA). Other authors [4] present also following types: case-based reasoning (CBR), rule-based filtering (RBF). In this section we present the following filtering methods: DF, CF, CBF and HA in more details, and application of CBR and RBF will be only mentioned at the end of this section.

BASIC MATHODS

We can distinguish three basic information filtering methods: DF, CBF and CF. DF uses a stereotype reasoning [6] in recommendations and is based on the information stored in the user profile that contains different demographic features. Stereotype reasoning is a classification problem that is aimed at generating initial predictions about the user [5]. The demographic data that is an element of the user data, contains the following elements: record data (name, address, e-mail, etc.), geographic data (zip-code, city, state, country), user's characteristics (sex, education, occupation), and some other customer qualifying data. The DF has however some disadvantages [6], [7]: for many users generalizations of the user's interests associated with some demographic attribute values may be too general; they do not provide any individual adaptation, also when the user interests tend to change over time; users are quite often reluctant to submit demographic information or lie in this matter. These disadvantages may be overcome by application of other recommendation methods such as CF, CBF or hybrid approach.

CBF takes descriptions of the content of the previously evaluated items to learn the relationship between a single user and the description of the new items [6]. CBF was applied in many interface agents that were developed at MIT [2]. The interface agent first computes the distances between the current state and each past state that is stored in the memory and contains corresponding user actions. Then the agent recalls by the past state that resembles the current one. CBF approach enables personalized and effective recommendations for particular users, but has also some disadvantages: content-based approaches depends on so called objective description of the recommended items; it tends to overspecialize its recommendations; content-based approach is based only on the particular user relevance evaluations, but users usually are very reluctant to give them explicit, so usually other implicit, possibly less adequate, methods must be used.

CF makes automatic predictions (filtering) about the recommended items by collecting and using information about testes of other users (collaboration) [10]. CF based recommender systems are using usually user item rating matrix that is used for both: identifying similar users and recommend items highly ranked by those users. The other approach called also item-based approach uses item-item matrix to determine the current user taste according to selection one item. The main advantages of collaborative filtering over the CBF architecture are following [6]: the community of users can deliver subjective data about items; collaborative filtering is able to offer novel items, even such that user has never seen before; collaborative recommendation utilizes item ratings of other users to find the best fitting one. Collaborative recommended agents have also some disadvantages: when the number of other similar users is small then the prediction is rather poor; the quality of service for users of peculiar tests is also bad; this is rather difficult to get sufficient number of similar users to be able to make proper predictions; observe their users and then apply some machine learning mechanisms to draw the recommendation; lack of transparency in the process of prediction and finally the user's personal dislike may be overcome by the number of other similar users opinions.

The CF could overcome by applying the hybrid solution, for user interface recommendation for web-based information system presented in [8] the disadvantages mentioned above do not influence it much. First, we can assume that web-based systems always have quite many similar users. Second, when the prediction does not fit the user, he is able to personalize the interface manually.

HYBRID AND OTHER RECOMMENDATION APPROACHS

The disadvantages of each of the above mentioned recommendation approaches could be overcome by applying HA. For example the disadvantage of the insufficient number of the similar users at the early stages of the system operation using CF may be overcome by application of the demographic stereotype reasoning.
For example in the user interface recommendation was based on the mixture of the DF and CF [7], [8]. Basically the HA [8] is a combination of demographic, collaborative and content based recommendation. However other types of recommendations that are based on: user emotions, user platform or context of use may be also considered.
We can distinguish at least two types of the HA, first that builds the recommendation basing on each single approach and second, that integrates the knowledge from each single approach before determining the recommendation. For example in the movie recommendation using the former approach we should first determine the lists of recommended movies using DF, CF and CBF separately and then combine these three lists. Using the later approach we modify the stereotype reasoning or fuzzy reasoning rules according to the data or rules of other users (CF) or ranked movies (CBF). Then the final recommendation is determined using these modified rules.
Beside above mentioned recommendations: DF, CF, CBF and HA, we should also mention other ones, such as: platform, situation or emotion based, which could be combined under single name case-based reasoning (CBR). These recommendations may be dealt in two different ways. The first one is based on the expansion of the subject's attribute set with the attribute concerning platform, situation or emotions in standard DF, CF or CBF. The second method treats these recommendations as separate ones, with their own knowledge acquisition methods and reasoning rules.

ARTIFICIAL IMMUNE SYSTEMS (AIS) APPLIED IN RECOMMENDER SYSTEMS

AIS may be used in several different ways [3], as model for biological immune system explanation, exploitation and prediction or as an abstraction of some immunological processes. However AIS is a relatively young field it has already pretty many different applications: change detection (i.e. made by computer viruses); fault detection and diagnosis (i.e. applied in building hardware fault-tolerant systems); a means of implementing the negative selection
According to [1] application of AIS in collaborative based recommender system works in the following steps (shown in Fig. 1):
1. The system stores some people's preferences in the database;
2. Each user inputs his or her preferences for some items (i.e. movies), and requires recommendations on some items that he or she has not seen before;
3. AIS selects a group of people (antibodies) who has similar preferences with the particular user (antigen);
4. The weighted average of the preferences for that group of people is calculated by the CF to generate recommendations which the user requires.
Generally the AIS model [1] is controlled by the Equation (1), which describes the antigen concentration changes , i.e. it increases with antibody's matching the antigen and decreases in the case when antibody is matching other antibodies; there also exist the death rate that decreases the value when the antibody is neither good or bad.

$$\frac{dx_i}{dt} = k_1 m_i x_i y - \frac{k_2}{n} \sum m_{i,j} x_i x_j - k_3 x_i \qquad (1)$$

Where, y represents the antigen concentration; x_i represents the antibody concentration of antibody i, x_j represents the concentration of antibody j; $m_{i,j}$ represents the affinity between the antibody i and j; m_i represents the affinity between the antibody i and the antigen; k_1, k_2 and k_3 represents some weights.
We can find quite many algorithms for determining affinity between antibodies (correlation coefficient) - Kappa and Kendall tau [1] or Person's coefficient or cosine similarity measure. Weighted kappa coefficient that measures of ratings between two users practically may be calculated using the Equation (2).

$$k = \frac{1}{n} \sum_{i=1}^{g} \sum_{j=1}^{g} w_{ij} f_{ij} \qquad (2)$$

Where g is the number of categories (i.e. rates given to the movies) that could be given for items, n is the number of observations, f_{ij} is the number of rating agreements for the cell in row i (representing ratings of the first user) and column j (representing ratings of the second user); w_{ij} represents the value of weight (see Equation (3)) for the cell in row i and column j.

$$w_{ij} = 1 - \frac{|i-j|}{g-1} \qquad (3)$$

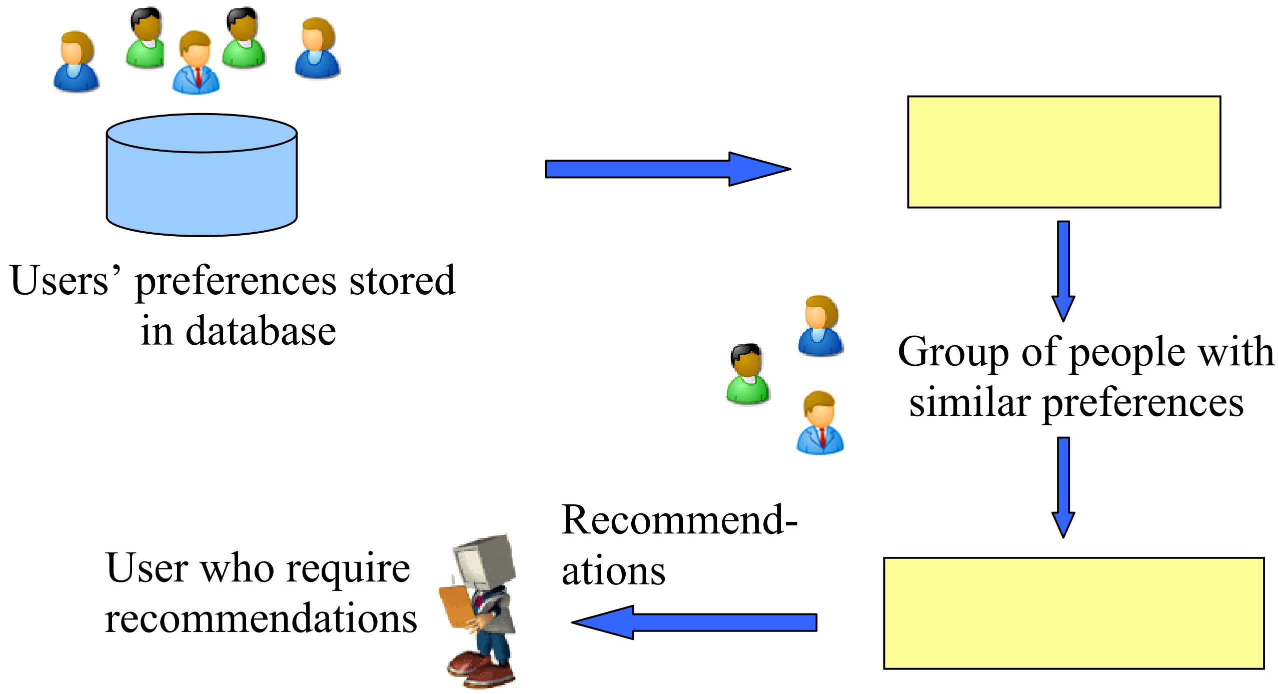

Figure 1: AIS architecture applied in recommender system.

To generate recommendation we should first determine the group of users with similar preferences using weighted kappa coefficient measure that should be greater than specified threshold value ε. Then predicted rating for the new user and item *a* is determined according to the Equation (4):

$$Rating\quad prediction(a) = \frac{\sum_{i=1}^{n} weight_i \times Rating_i}{\sum_{i=1}^{n} weight_i} \qquad (4)$$

Where, $weight_i$ represents the weight of the i-th antibody, such that $weight_i = concentration_i$ (of the i-th antibody giving the rating for the item a), $weight_i = 0$, (the i-th antibody did not deliver rating the item a), $concentration_i$ represents the concentration of the i-th antibody (a way of its determination will be shown below), $Rating_i$ represents the score which the i-th antibody voted the item a.

IMPLEMENTATION, TESTS AND RESULTS

In order to verify AIS method effectiveness we implemented Reporter system based on MediaWiki software. To get articles database we downloaded data dumps from one of the Wiki's projects, namely over 2000 articles from Polish WikiNews portal. In order to get articles rates from the users, articles ratings module was also implemented. Users could mark an article using the following scale:1 – poor; 2 – average;3 – good; 4 – very good; 5 – excellent. Besides rating articles users could also rate 4 different layouts, using the same scale as articles ratings, of the Reporter system called: "sport", "mono-book", "portal" and "multimedia". All articles and layouts ratings gave by the users were stored in the database.

TESTS

The group of 22 users, mainly students of the third year of the Faculty of Computer Science at Wroclaw University of Technology took part in our test which was conducted to verify the effectiveness of AIS Method. Tests were divided into two parts. In the first part users were asked to fill in registration form giving some personal data (mainly their age and interests), and then log in into the system. They were asked to get familiar with the Reporter system, to read articles and to rate those articles. They had free hand with choosing the articles to rate.
In the second part of these tests all the users were asked to rate over 20 the same articles from prepared list. They also gave rate application layouts. Having these article and layout rates we could compare them with the predicted rate calculated by AIS method. If the rates were very close to each other or the same, we could judge AIS method effectiveness as very high. If there was a quite big discrepancy in user rates and AIS prediction rates, we judged AIS method as very low.

RESULTS

In order to verify the obtained results we used the precision accuracy measure (Equation 5) that could assess the quality of predictions made by AIS method [1]:

$$1-\frac{\sum_{i=1}^{n}\left|\frac{prediction-actualVote}{g-1}\right|}{n} \tag{5}$$

where: n – number of articles; *prediction* – article's rate predicted using AIS method; *actualVote* – actual user rate of the article; g – number of rates (categories).
The calculations were made for different threshold values p. Having weighted kappa coefficient between two users, we compared it with the p value, which determined the affinity of these users. Users with the weighted kappa coefficient lower then assumed threshold p were eliminated. If the weighted kappa coefficient between users was higher than the assumed value p, we treated them as similar users. In that way we could have the group of similar users for which we were able to calculate articles predictions rates. These groups of users differed from others depending on assumed p value. Along with the growing p value, the amount of users selected in the AIS method decreased. The calculations were conducted for the following threshold values: $p = 0{,}7$; $p = 0{,}75$; $p = 0{,}8$; $p = 0{,}85$.

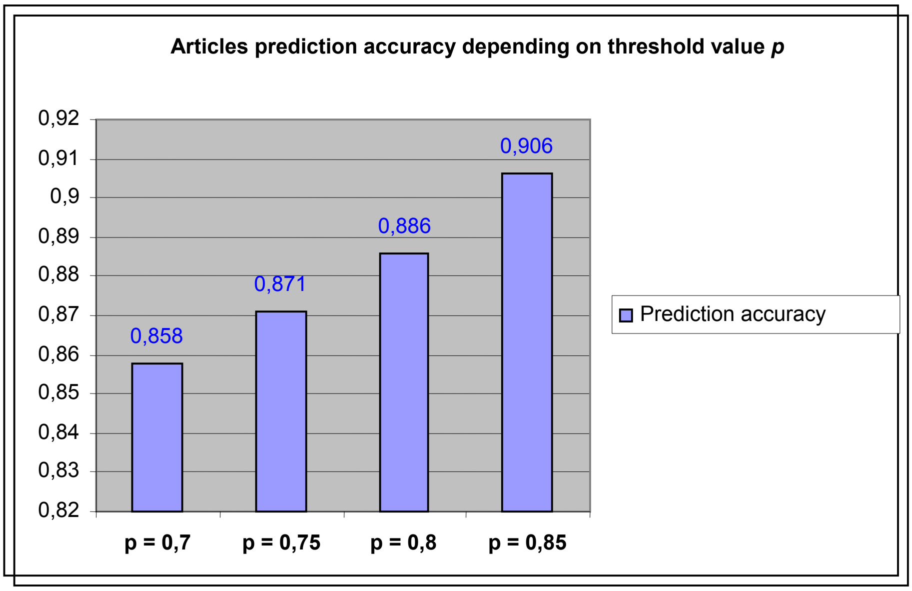

Figure 2: Articles prediction accuracy depending on threshold value p

When correlation between users increases with growing threshold value p article prediction, the accuracy increases as well. These results were satisfied for all p values (affinity of selected users groups were good enough). With the threshold value 0.85 the results were very good. We could observe prediction accuracy at the level above 0.9 and average rates deviation below 0.5. It meant that average difference between user mark and our prediction was lower than one half of mark.

SUMMARY

The application of AIS method for article recommendation proved to be very effective recommendations. Similar test were conducted for interface layouts. We wanted to check if users having similar preferences about articles' content could have similar preferences about interface layouts. In this case groups of similar users were selected based on their article notes, but we made predictions for interfaces ratings. We could compare real users' rates of interfaces layouts with the ratings predicted using AIS method.

Layouts prediction accuracy and layouts average rates deviation varied with increasing p value. The tendency wasn't the same as it was with the articles' rates. The results were very good and satisfied for $p = 0.85$. For other p values these measures varied a lot. It means that there wasn't so strong dependency between user's correlation coefficient and prediction accuracy measures for interfaces rates. In some way users' interests could have had influence on users' preferences regarding application layouts, however it was more independent.

REFERENCES

[1] Chen Q., Aickelin U., Movie Recommendation System using an artificial immune system, Poster Proceedings of ACDM 2004 Engineers' House, Bristol, UK

[2] Fleming, M., Cohen, R.: "User modelling in the design of interactive interface agents"; Proc of the Seventh International Conference on User Modelling**,** (1999) 67-76.

[3] Garrett S.M., How Do We Evaluate Artificial Immune Systems?. Computational Biology Group, Department of Computer Science, (145-178).

[4] Kazienko P., Kiewra, M.: "Personalized Recommendation of Web pages". International Series on Advanced Intelligence, 10, (2004) 163–183.

[5] Kobsa, A., Koenemann, J., Pohl, W.: "Personalized Hypermedia Presentation Techniques for Improving Online Customer Relationships". Knowledge Eng. Rev. 16(2), (2001) 111-155.

[6] Montaner, M., Lopez, B., de la Rosa, J.P.: "A Taxonomy of Recommender Agents on the Internet"; Artificial Intelligence Review 19, (2003) 285-330.

[7] Nguyen, N.T., Sobecki, J.: "Using Consensus Methods to Construct Adaptive Interfaces in Multimodal Web-based Systems"; Universal Access in Inf. Society 2(4), (2003) 342-358.

[8] Sobecki J.: "Hybrid Adaptation of Web-Based Systems User Interfaces". Proc. of ICCS 2004, Krakow, Poland, Lecture Notes in Computer Science 3038, (2004) 505-512.

[9] Timmis J, Knight T., De Castro L.N., Hart E., An Overview of Artificial Immune. Systems. In R Paton, H Bolouri, M Holcombe, J H Parish, and R Tateson, editors, *"Computation in Cells and Tissues: Perspectives and Tools for Thought"*, Natural Computation Series, pages 51-86. Springer, November 2004.

[10] Wikipedia, articles on Artificial Immune Systems and Collaborative Filtering. Downloaded on Octoer 2006 http://en.wikipedia.org