Personalized, affect and performance-driven Computer-based Learning

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Abstract: The growing prevalence of Internet during the last decades has made e-learning systems and Computer-based Education (CBE) widely accessible to a great amount of people with different backgrounds and competences. Due to these rapid advances in computer technologies, there has been a great shift from conventional, low interaction and printed learning content to high-level, computerized interactions for Computer-based Education. The above has led to the need for personalized systems, able to adapt their content for a variety of learner's abilities and skills. A key factor in content personalization is the degree to which the material itself keeps learners engaged over the course of the interaction: a CBE system has to cater for enough flexibility and be endowed with the ability to infer the degree to which the learner is engaged in the interaction and also be in the position to take decisions regarding the triggering of those adaptation mechanics that will keep the learner in a state of high engagement, maximizing, thus, the knowledge acquisition. A straightforward approach in content adaptation is the monitoring of levels of engagement, frustration and boredom in a learner and the subsequent adaptation of challenge levels imposed by the learning material. In this paper, we investigate the use of Collaborative Filtering, in order to build a content adaptation mechanism, based on recommendations on learner affect states. We showcase results on an interface developed specifically for the purposes of this research. The system's objective is to offer optimized sessions to the learners and improve their knowledge acquisition during the interaction with the system.

1 INTRODUCTION

The increasing popularity of technology and the amount of available resources on the Web, especially for Computer-based Education (e-learning systems, serious games, on-line courses) has made imperative the use of personalized systems that will be able to adjust their content to cover a wide range of needs in education. In order to handle the needs of all possible learners, Collaborative Filtering (CF) and recommendation systems are scientific domains with a great potential to be applied in order to generate robust and efficient adaptive systems. In this paper, a novel, Computer-based Education recommender system is proposed, with final scope to take advantage of learner cognitive and affective states and, thus, optimize and personalize the delivery of content. Furthermore, a serious game called "Learnin' platform" was created for the purposes of this research, as a testbed platform, in order to perform the evaluation of our concept.

Every time new learners are interacting with the "Learnin' platform", the game engine, ideally, should re-direct them to the level of difficulty in which the learners will be more engaged and help them remain to their state of flow. The term flow was introduced in (Csikszentmihalyi, 1975), (Nakamura and Csikszentmihalyi, 2014), (Csikszentmihalyi, 1996). It was used to describe the positive feelings and the enjoyable experiences of individuals during the execution of a task. By definition, flow is the psychological state in which an individual experiences motivation, efficiency and happiness. A system that motivates students to continue and enjoy the learning process is a critical point in Computer-based Education and it is the case study of this paper. The learning experience can be represented by two dimensions, the skill of the learners and the challenge presented to them. Achieving a balance between these two parameters, a positive effect on the educational process

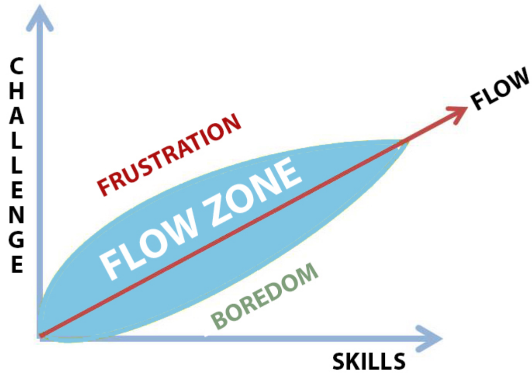

Figure 1: 2D flow zone model with platform competence and learner skills.

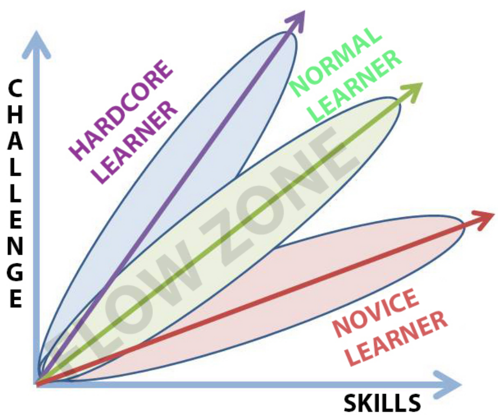

Figure 2: Different flow zones for different learners.

can be provoked, allowing a higher engagement in the learning activity and improving concentration, involvement and happiness of the learners. The incorrect selection of learning content could provoke frustration or boredom, depending on whether the challenge presented is too high or too low respectively. These two important variables are examined in this study. Fig. 1 depicts the correlation of learner skills and platform challenge. Different learners have different learning flow zones and the system has to detect those different zones and to recommend different learning content accordingly. Fig. 2 illustrates the flow zone for different learners.

The contribution of this paper is two-fold: firstly, we propose the adoption of learners' affective states as the explicit voting for the recommendation systems and, secondly, a novel database is introduced, in order to evaluate the proposed technique. The implemented CF will propose to new learners levels of difficulty which will keep them in their flow zone.

The structure of the remainder of this paper is as follows: In Section 2, the related work for CBE, recommendation systems and flow theory in education is presented. Section 3 describes the collaborative filtering algorithm used for evaluating upon the database and creating the personalization system for the "Learnin' platform" and the baseline algorithms used for evaluation as well. Section 4 describes the "Learnin' platform" which was used as a testbed platform for evaluating the proposed algorithm and for creating our database while in Section 5 the database architecture is described. In Section 6, experimental results from the proposed algorithm are shown. Finally, Section 7 contains the conclusion of this study.

2 RELATED WORK

Our work relates to several areas of research such as personalization in Computer-based Education (Milicevic et al., 2011), recommendation systems (Y. Koren and Volinsky, 2009), (Sun et al., 2014) and theory of flow (Liao, 2006). Several approaches within the Computer-based Education community implemented recommendations systems algorithms such as collaborative filtering (Y. Koren and Volinsky, 2009) with goal to personalize systems to a plethora of individual needs and skills.

Recommender systems (RSs) play an increasingly important role in our daily lives. They use preferences of a large bank of users to help individuals identify content of interest, from a great plethora of choices more effectively. RSs' goal is to automatically propose to a user items that might be of interest to him/her. They have been successfully applied on Computer-based Education for recommending which learning content is sufficient for learners to study next and contribute to learners progress towards particular goals (Milicevic et al., 2011), (Segal et al., 2014), (Bachari et al., 2011).

Collaborative Filtering was previously used in the educational domain for personalizing learner profiles (Bobadilla et al., 2009). CF can be defined as following: Given a matrix R that represents a known set of M learners (users) preferences to N items (e-learning content), recommend to each user a list of items that are ranked in a descending order of relevance to the users interest. Up to our knowledge, this is the first time that the combination of CF algorithms and affective states as explicit preferences is implemented.

A lot of works can be found in the literature considering recommender systems and collaborative filtering. Among them, probably the most popular, is the work done by Koren et al (Y. Koren and Volinsky, 2009). In this work, the implementation of Singular Value Decomposition (SVD)-based Matrix Factorization (MF) in order to create a recommender system using Netflix database. MF algorithm decomposes the rating matrix into user and item latent matrices. The re-decomposed matrix can be used for finding the votes for the unknown items for every user. Cross-validation methodology was applied, for tuning λ, which is a parameter used during the MF optimization and helps the system avoiding over-fitting. Furthermore, authors tried to address items and user progress over time by making use of temporal dynamics and applying user and item biases deviations to the re-decomposition of the rating matrix. The proposed system won the 2007 and 2008 Progress Prize of Netflix challenge.

In (Salakhutdinov and Mnih, 2011), authors proposed a probabilistic matrix factorization (PMF), for decomposing the rating matrix of users-items using the Neflix database. A probabilistic way to tune the regularization parameter λ for the matrix decomposition was proposed. Finally, they combined the PMF model with Restricted Boltzmann Machines models in order to improve the performance of the system. Their approach was proved to perform well on very sparse and imbalanced datasets and in handling the over-fitting problem of the optimization as well.

In (Milicevic et al., 2011), authors proposed a programming tutoring system called "Protus", developed for teaching Java programming language. The main scope of "Protus" is to recommend the best possible material for the e-learners based on their background and skills. The proposed system consists of three basic modules. When learners were registered to the system, a short survey was performed with aim to reflect their preferred learning style. Then, a clustering technique is applied in order to create clusters of learners based on their learning style. Finally AprioriAll algorithm (Tong and Pi-lian, 2007) was used to find frequent sequences of learning materials patterns in each learning style and make the recommendation accordingly. These generate recommendations based on the collaborative filtering approach.

In (Segal et al., 2014), authors proposed "EduRank", a system for personalizing educational content for learners, which combines collaborative filtering and social choice theory. The algorithm constructs a difficulty ranking over questions and aggregates the ranking of similar students, as measured by different aspects of their performance on past questions such as grades, number of retries and time spent solving questions. Thus, the first step of the algorithm is to estimate the similarity of learners and then, combine the rankings of the similar users to propose it to the target user.

In (Bachari et al., 2011), authors presented three main models to achieve the goal of personalization, which are domain model, tutor model, and student model. The domain model contains the knowledge about the learning content structure such as chapters and topics of different subjects while student model holds the learners characteristic including their preferences, identity. These can be used to adapt the content and teaching styles. This research has added tutor model to enhance the personalization system from the previous research. The tutor model represents the teacher's knowledge for teaching each concept. The decision and identification model used in this work was based on Dynamic Bayesian Network (DBN). DBNs were used with a goal to introduce to the learner the contents and materials of interested in according to the score obtained by the learner using the Myers-Briggs Type Indicator (MBTI) test.

In (Bergner et al., 2012), authors proposed a model-based estimator of accuracy levels of learners performance and skill levels on real and simulated datasets. Furthermore, they established a relationship between collaborative filtering and Item Response Theory methods and demonstrated this relationship empirically.

In (Toscher and Jahrer, 2009), authors make use of KDD Cup 2010, an educational database (J.Stamper et al., 2010) which contains questions from algebra topic in several steps and difficulty and the learner performance as well (answer, time spent etc.). Authors implemented several methods to model the database. Firstly, they applied K-Nearest Neighbors in order to find the most similar users. Authors also implemented Singular Value Decomposition (SVD) in order to decompose the matrix of users and questions-steps using stochastic gradient descent. Authors found out that SVD does not work well with sparse data so they proposed an enhanced algorithm, called Factor Model (FM) in which they add bias models (as in (Y. Koren and Volinsky, 2009)) in the re-decomposition of the user-steps matrix. Finally, a Neural Network architecture called Restricted Boltzmann Machines was applied to ensemble the mentioned models.

In (Liao, 2006), a study of flow theory in human computer interaction was performed. This study consists of two main models: Firstly, an empirical investigation of the theoretical construct of flow theory in Computer-based Education which tried to identify the main components of flow during the learning process and, secondly, a study of the impact of interaction between three different categories of flow. Those categories were: learner to instructor interactions, learner-learner interactions and finally learner-interface interactions.

3 RECOMMENDATION SYSTEMS

The novelty of the proposed research is mainly due to the adoption of learners' affective states as explicit preferences for the recommendation systems and collaborative filtering. In order to consider the affective state of the user in the approach presented in that work, a relevant parameter has been defined. This parameter merges the values derived from the theory of flow (Liao, 2006) (namely, boredom, frustration and engagement) in a single value, formalized by a so called energy function. This function is based on an assumption that learners are remained in their flow state when they are more engaged while boredom and frustration adversely affect it (Csikszentmihalyi, 1991), which is also depicted in Figure 1. When learners are in flow zone, psychic entropies like frustration and boredom are not occur while engagement is maximized. Thereby, the introduced energy function concatenates the three affective states into one value. Thus, the following formula was applied using the learner annotations in order to concatenate the affective states:

$$f_i(l) = C + \alpha \times E_i(l) + \beta \times B_i(l) + \gamma \times F_i(l) \qquad (1)$$

Where l corresponds to the learning session, i is learner's unique *id* and E, B, F the affective state levels (Engagement, Boredom, Frustration) and they take values from 0-5, while parameters α, β, γ are tuned to $\alpha = 1, \beta = -1, \gamma = -1$. The static term C was introduced in order to keep the energy function positive. A default value was set to $C = 10$. This was done due to the implementation of Non Negative Matrix Factorization. The scope of this study is to redirect learners to levels of difficulty in which their energy function will be maximized. In order to achieve so, Non-Negative Matrix Factorization is applied with scope to optimize the energy function for each learner.

3.1 Non-Negative Matrix Factorization

As soon as the concatenation between the affective states was performed, the personalization system was ready to be trained using the database as is described in Section 5. A separation of learning sessions among the different subjects was applied. For each subject, a 2-dimensional matrix was constructed (with learners as rows and levels of difficulty as columns, representing the challenge presented to the them). Each matrix contained the energy function value for all learners as explicit preference to 9 different levels of difficulty. For every subject a matrix was constructed with size 31×9, where 31 is the total number of the learners and 9 is the number of difficulty levels for every subject.

Subsequently, the next step was the implementation of the Matrix Factorization algorithm (Lee and Seung, 2001) (Lee and Seung, 1999). MF is a linear algebra algorithm which, given a matrix R of learners voting preferences over a plethora of items, and a desired rank k, its endeavor is to decompose the matrix into W and H, so as the matrix $A \approx WH$ to be a good approximation of matrix R. This matrix approximation A can be used in order to make recommendations to the learner for the unknown items (levels of difficulty) of the matrix. Factorization works based on the following principle - that both the user and the items from matrix R should be represented in the same way. MF maps learners and items into a common space "k". The rank space "k" is also mentioned in the literature as latent factors. High correlation between item and user latent factors can lead to a recommendation for the learner. In this study we made use of Non-Negative Matrix Factorization (NMF) method, which is summarized below:

- Given a non negative matrix R, the goal of NMF is to minimize $||R - WH||^2$ with respect to W, H with the constraint to be that $W, H \geqslant 0$.
- NMF is a nonconvex problem.
- NMF is in fact a SVD based algorithm .
- For Non-negative Data, NMF provides better Interpretation of Lower Rank Approximation.
- The main difference with the SVD is that both W, H are mandatorily positive.
- SVD yields unique factors whereas NMF factors are non-unique. This makes NMF more suitable for privacy protection algorithms.
- The non-negativity rules of NMF algorithm makes the resulting matrices easier to inspect. Since the problem is not exactly solvable in general, it is commonly approximated numerically.

For the sake of this proposed system, a python implementation of Non-Negative Matrix Factorization (NMF) was applied. The objective function of the minimization problem that was implemented is the following:

$$f = 0.5 * ||R - WH||_F^2 + \alpha * \lambda * ||W||_1 + \alpha * \lambda * ||H||_1 + 0.5 * \alpha * (1 - \lambda) * ||W||_F^2 + 0.5 * \alpha * (1 - \lambda) * ||H||_F^2 \quad (2)$$

where λ is parameter that helps avoid the over-fitting, α a constant that multiplies the regularization terms and F stands for Forbenius norm. Additional info about the optimization equation can be found here [1].

In our system, matrix R contains the energy function values of the learners over the several difficulty levels. The re-decomposed matrix $A \approx WH$ can conceal hidden values of energy function values in unknown levels of difficulty for learners in the database, as well as, for new learners that will interact with our "Learnin' platform". When a new learner enters into the platform, and after every performed session, the system's target is: By making use of the provided annotation (for affective states) to estimate what the energy function values of the learner will be for the rest of the difficulty levels. The NMF algorithm is implemented using the database matrix, enlarged with the addition of the new learner's vector (contained the energy function values gathered so far). The recommendation for a new learner then can be formalized as follows:

$$a_{ik} = w_{ik} * h_{kr} \quad (3)$$

where w_{ir} are the latent factors of the learner and h_{rk} are the latent factors of the levels of difficulty. The above formula approximates learner i energy function value for the specific difficulty level r. In the end, the system always re-directs the learner to that level of difficulty k with the highest approximated energy function.

4 "LEARNIN' PLATFORM"

The testbed platform used in our study is a serious game called "Learnin' platform" developed specifically for the purposes of this research from Maastricht University. The original "Learnin' platform" is available on Github[2]. The platform consists of two major functionalities: 1. The teacher account functionality, with which tutor has the ability to add new subjects and questions of varying types, levels of difficulty and also tune maximum available time for the answer to be given by the student, 2. The student account functionality which performs the learning sessions of "Learnin' platform". The learner entering with student credentials can choose between 4 different default subjects ("Math", "Sports", "Geography", "History"). For the purpose of data acquisition, every time the learner is playing a specific subject, the level of difficulty is changing randomly. The levels of difficulty are in total 9 (from 1-9). Throughout the learning session, the learner is informed about the current level, the current score and the time left for answering the question. A detailed description of the testbed platform interfaces is the following:

- An introduction interface, where the two different accounts (teacher and student) are presented in two different buttons, (Fig. 3).
- When the learner presses the student scene button, the Log in/Sign up interface is presented.
- Students add their information (demographics) in sign up scene in order to be able to login.
- Subsequently, students are directed to subject interface where they can choose a subject among 4 different courses ("Math", "History", "Sports", "Geography") and then they can start a new game.
- Then, the learning session begins and the learners have to answer 7 different questions (Fig. 4).
- During the learning session, questions, the possible answers and a status bar with information for the learning session is rendered to the learner.
- During the learning sessions, different sounds and emoticons are used with scope to provoke and boost learners reactions.
- After each session, learners were asked to annotate their affective states, levels of engagement, boredom and frustration in scale of 0-5.
- The next scene is the result panel interface, which informs learners about their performance during the session.
- Finally, learner has the choice to either logout or continue with a new session. In the latter case, learner has to choose a subject and to start the new session.
- Teacher interfaces are not presented since this is out of the scope of this study.

The core idea of this paper is to introduce a personalization mechanism that will change the difficulty levels of the system automatically based on the flow of the learner that interacts with the platform. Thereby, "Learnin' platform" was developed firstly for the data gathering process, and secondly for the

[1] http://scikit-learn.org/stable/modules/generated/sklearn.decomposition.NMF.html

[2] https://github.com/kristosh/Mathisis-platform

Figure 3: Learnin' Introduction interface

Figure 4: Learnin' learning session interface.

implementation of our personalization mechanism. In the following section the data architecture used for training our algorithm is presented.

5 DATASET ARCHITECURE

The dataset consists of students from Maastricht University, Netherlands, who voluntarily played our "Learnin' platform". They were bachelor and master students 21±7 years old with technical background. For every student, 4 learning sessions of 4 different courses were captured. After each learning session, users were asked to assess the degree of engagement, frustration and boredom they experienced. The assessments were given in the form of ratings from 0 to 5. The analysis presented in this paper is based on 31 users (19 males and 12 females) playing 16 learning sessions from our "Learnin' platform". The lighting conditions during the capturing procedure were typical for an office environment and a Logitech HD 720p camera was used. The visual feedback of the learners captured for future work and further analysis of learners affective states. The database protocol for gathering the data was inspired from the works done in (Yannakakis et al., 2009) (Shaker et al., 2011).

- Firstly, a small oral introduction to the participants was performed with some information about the procedure that would be followed.
- Participants were told that during the experiment they will have to play 16 learning sessions in total.
- The duration for the whole experiment per each participant was 26±5 minutes.
- Due to time limitations, students were asked to play just 4 sessions per subject.
- The system automatically changed the difficulty levels based on the performance of the learners.
- In order to acquire data from different levels of difficulty, the approach applied is based on the score obtained in the previous session. Initially, the first level is chosen randomly between levels 1 to 3. Afterwards, the increase of the level is based on the score obtained by the user. In this way, the user is asked to answer questions related to levels 4 or 5, 6 or 7 and 8 or 9, depending on whether the learner passed or failed the previous test.

The "Learnin' platform" consists of two SQLITE databases. Firstly, a database which contains all the questions of the platform and secondly a database which contains all the information about the learners during the learning sessions.

6 EXPERIMENTAL RESULTS

This section discusses the findings which emerged from the evaluation of the algorithm, described in section 3. The core experiment setup of this work, is the following: 31-fold cross validation was performed for each of the 4 datasets for the different subjects. Cross-validation randomly splits the dataset 31 times into two sets: the training set and the evaluation set (30 samples for training and 1 sample for testing). In the evaluating sample, randomly, an energy function value was deliberately removed and the evaluation scope's was to estimate this missing value. Table 1 and as well as, Figs. 5, 6, 7, 8 render the root mean square error between the initial value we removed from evaluating set for all subjects and the approximation value introduced from NMF algorithm (for all subjects) for several values of rank k after cross validation. An exhaustive search was performed in order to calculate the best parameters of NMF. In Table 2, the chosen parameters for NMF are illustrated.

Experimental results for NMF algorithm, concealed a promising approximation of the hidden energy function values during the cross-validation pro-

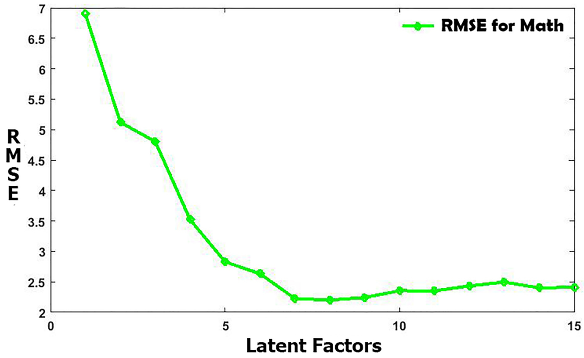

Figure 5: Root mean square error for the subject Math

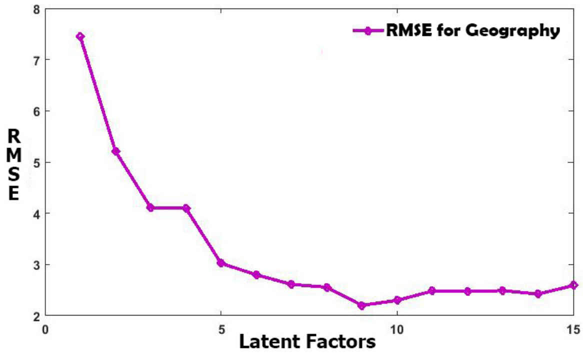

Figure 6: Root mean square error for the subject Geography

cess. Thereby, a striking observation which emerged from the research done in this work was that Non-Negative Matrix Factorization could be successfully applied as a recommendation system in our "Learnin' platform" (and therefore in Computer-based Education systems) efficiently estimating the energy function values of the learners affective states. Furthermore, the whole procedure of NMF energy value estimator could lead to optimized selection of levels of difficulty based solely on affective state knowledge.

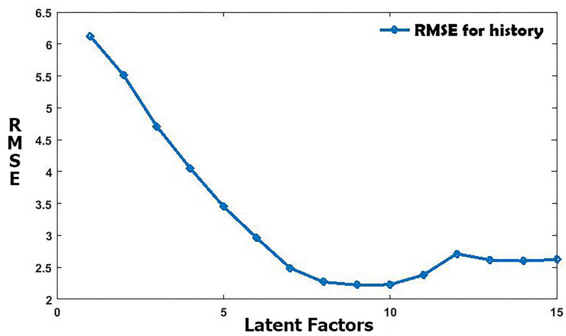

Figure 7: Root mean square error for the subject History

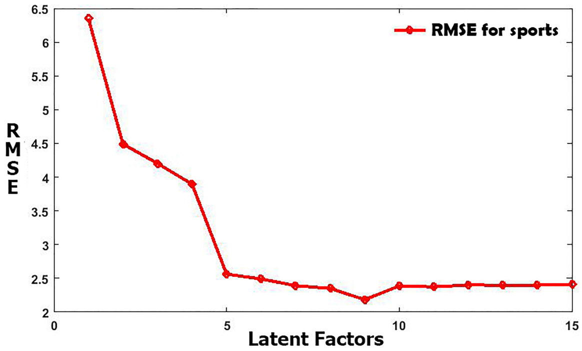

Figure 8: Root mean square error for the subject Sports

7 CONCLUSIONS & FUTURE WORK

The presented study introduced several noteworthy contributions to the domains of recommendations systems in education. Firstly, up to our knowledge, this was the first study performed on learners affective states and Non-Negative Matrix Factorization during the interaction with Computer-based Education. We made use of learner affective states as the user explicit preferences over a set of learning content. A Collaborative Filtering algorithm called Non-Negative Matrix Factorization was implemented in order to develop our system by taking advantage of learners affective states when interacting with the system's learning content. Secondly, a novel database for evaluation of the applied technique was introduced. The results of this study show that NMF algorithm could be successfully applied to the constructed database with scope to generate a robust and efficient personalised Computer-based Education system. Furthermore, the novel serious game that used for gathering the database is presented. The outcome of this study also introduced a link between theory of flow and recommendation systems and it will serve as a base for future studies about the relationship of computer vision-based affective states of a learner and the calculated learners' latent factors from decomposition algorithms. The proposed NMF algorithm, can substitute the current platform's functionality for the difficulty-level shift after each learning session. Finally, future work will be focus on enhancement of the affective states annotation by incorporating key moments detection and annotate those moments automatically with an emotion recognition module which could make use of Deep learning architectures.

Table 1: RMSE for NMF, after cross-validation

Subject	k=3	k=5	k=7	k=9	k=11	k=13	k=15
History	4.708	3.454	2.489	2.223	2.380	2.615	2.622
Sports	4.203	2.563	2.392	2.184	2.374	2.399	2.408
Math	4.803	2.830	2.227	2.243	2.352	2.497	2.412
Geography	4.112	3.022	2.611	2.201	2.481	2.489	2.588

Table 2: Chosen parameters for NMF

alpha	0,1
l1 ratio	0,6.
solver	cd
random state	0

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