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A New Approach to Modelling Students' Socio-Emotional Attributes to Predict Their Performance in Intelligent Tutoring Systems

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Abstract

Intelligent Tutoring Systems (ITS) are computer-based learning environments that aim to imitate to the greatest possible extent the behavior of a human tutor in their capacity as a pedagogical and subject expert. One of the major challenges of these systems is to know how to adapt the training both to changing requirements of all kinds and to student knowledge and reactions. The activities recommended by these systems mainly involve active student performance prediction that, nowadays, becomes problematic in the face of the expectations of the present world. In the associated literature, several approaches, using various attributes, have been proposed to solve the problem of performance prediction. However, these approaches have failed to take advantage of the synergistic effect of students' social and emotional factors as better prediction attributes. This paper proposes an approach to predict student performance called *SoEmo*-WMRMF that exploits not only cognitive abilities, but also group work relationships between students and the impact of their emotions. More precisely, this approach models five types of domain relations through a Weighted Multi-Relational Matrix Factorization (WMRMF) model. An evaluation carried out on a data sample extracted from a survey carried out in a general secondary school showed that the proposed approach gives better performance in terms of reduction of the Root Mean Squared Error (RMSE) compared to other models simulated in this paper.

Keywords: Intelligent tutoring system, Impact of emotions, Social influence, Socio-emotional intelligence, Matrix factorization, Student performance prediction.

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Contribution of this paper to the literature

This research investigates the field of predicting student performance in Intelligent Tutoring Systems by proposing an innovative approach based on the concept of socio-emotional intelligence. This approach incorporates, for the first time, the mutual influence of group work relationships and the impact of emotions felt during assessment sessions in form of attributes to enhance capacities such as motivation, attention and student commitment.

1. Introduction

Social and emotional intelligence, or socio-emotional intelligence, is the ability to integrate feelings, intuition and cognition to recognize, understand, manage, apply and express our emotions and social interactions at the right time, for the right purpose, in the right context and with the right person (Devis-Rozental, 2017; Devis-Rozental., 2018). It has also been defined as the ability to regulate emotions at the individual, group and cross-boundary levels (Peterson, 2015). It is considered by some researchers (Mupfumira & Nyaruwata, 2021; Nasir & Masrur, 2010; Pajibo, Dzikunu, & Asare, 2019; Piczon & Asis, 2019; Turi, Ghani, Javid, & Sorooshian, 2020) to be a predictor of academic performance and a prerequisite for academic achievement. Payton et al. (2008) describe social and emotional learning as a process by which all individuals (adults and children alike) acquire the skills necessary to, among other things, recognize and manage their emotions, establish and maintain positive relationships, and effectively manage interpersonal situations. As a result, it seems appropriate to take into consideration factors such as group work relationships and the effect of emotional state on a student's cognitive abilities in order to enhance and optimize learning in traditional learning systems in general and in Intelligent Tutorial Systems in particular. The practice of teaching in ITS should reflect our current understanding of the learning process, as marked by teamwork, and teaching methods should consider the affective and emotional state of students as a means of regulating motivation. In other words, tutors should consider the socio-emotional needs of students and adapt the interaction to have a positive impact on their performance. If these factors are taken into account in ITS, it should improve the learning environment and students' attitudes towards learning, and potentially improve learning outcomes.

This paper proposes a new approach that integrates the mutual influence of group work relationships and the impact of emotions experienced during assessment sessions in the form of socio-emotional attributes in a Weighted Multi Relational Matrix Factorization (WMRMF) model in order to provide increased accuracy in the prediction of student performance. Using these socio-emotional attributes, we aim to provide a measure of socio-emotional intelligence that can enhance abilities such as motivation and attention and engage students in the use of intelligent learning tutors. The approach proposed in this paper makes it possible to predict student performance by taking into account not only their cognitive abilities but also the impact of students' socio-emotional attributes.

1.1. Related Work

The first Matrix Factorization approach to student performance prediction based on the "KDD Challenge 2010" database was proposed by Thai-Nghe, Drumond, Krohn-Grimberghe, and Schmidt-Thieme (2010). They showed that student performance prediction could be consider the prediction of an assessment. In this approach, *student*, *task* and *performance* became *user*, *article* and *evaluation*, respectively, as presented in a classic recommendation system. The results of this study showed that the FM technique performed better compared to traditional regression methods such as Logistic Regression and Linear Regression. However, this basic technique can only be applied to a single relationship, that between a *student* and a *task*. Other scholars have adapted the classical FM approach in various ways, including Singular Value Decomposition (SVD) (Jembere, Rawatlal, & Pillay, 2017), Tensor Matrix Factorization (Thai-Nghe, Drumond, Horváth, Nanopoulos, & Schmidt-Thieme, 2011), Non-negative Matrix Factorization (NMF) (Hwang & Su, 2015). However, these approaches fail to take into account the secondary information included in the practical educational data, such as the data on different relationships associated with different domains of learning. Other improvements have been made to this basic technique over time. These include, among others, Multi-Relational Matrix Factorization (MRMF) and Weighted Multi-Relational Matrix Factorization (WMRMF) (Thai-Nghe & Schmidt-Thieme, 2015). However, these approaches did not incorporate the mutual influences in group work relationships and the emotions that students might experience when performing tasks. Notably, however, researchers report that, regardless of the subject, students who work in groups generally know more about what is being taught and retain the learning for longer than when the same content is presented using other teaching methods (Alhaj, 2015). In addition, emotion has been shown to have a major impact on an individual's judgment and reasoning (Damasio, 1995). Affective state also influences cognitive abilities such as attention, memory, problem solving and decision making (Isenman, 2018). Isenman (2018) argues that emotion has above all a prospective or motivational role. For these two reasons, we recently proposed in Assielou, Haba, Gooré, Kadjo, and Yao (2020a), an FM approach we called *So*-WMRMF, which combines students' cognitive capacities and the power of group relations in a Multi-Relational framework. Unlike the work carried out by most of the authors of the related literature, in this approach, the characteristic vector of a student is influenced by the weighted average of the characteristic vectors of all the participants in the working group. Specifically, this approach exploits the individual academic performance of each of the students in a work group as a factor of mutual influence. In Assielou, Haba, Kadjo, Yao, and Gooré (2020b) we further proposed an approach called *Emo*-WMRMF that models the impact of emotions that arise in a learning context and a framework for integrating these emotions in performance prediction. This approach is based on the control-value theory of achievement emotions proposed by Pekrun (2006), which is founded on the principle that a student can feel a combination of emotions at any particular moment. The various simulations carried out have shown that these two approaches make it possible to refine the precision of student performance prediction. However, what these two approaches failed to take into account was the synergistic effect of group relations and the emotions experienced either individually or in groups, since some social scientists, such as Willis and Cromby (2019), have shown that emotion is also relational.

In this paper, we propose a Weighted Multi-Relational Matrix Factorization and Socio-Emotional approach called *SoEmo*-WMRMF to better predict student performance.

1.2. State-of-the-Art

The approach proposed in this paper exploits the performance of the *So*-WMRMF and *Emo*-WMRMF models in the form of socio-emotional attributes. Therefore, this section presents the state-of-the-art of these two different approaches.

1.2.1. Weighted Multi-Relational Matrix Factorization (WMRMF) Approach

In the classical formulation of the Matrix Factorization or Decomposition problem, we assume the existence of a matrix $R \in \mathbb{R}^{S \times I}$ concerning S students and I tasks, which can be approximated by a product of two small matrices W_1 (student) and W_2 (task) as follows : $R \approx W_1 \, W_2^T$. In the matrix $W_1 \in \mathbb{R}^{S \times F}$, each row s represents a vector containing the F latent factors describing the student s. In the matrix $W_2 \in \mathbb{R}^{I \times F}$ each row i represents a vector containing the F latent factors describing the task i. The performance $\hat{p}_{si}$ of a student s carrying out a task i is predicted as follows:

$$\hat{p}_{si} = \sum_{f=1}^{F} w_{1_{sf}} \, w_{2_{if}} = w_{1_s} w_{2_i}^T \tag{1}$$

In Equation 1, w_{1_s} and w_{2_i} represent the vectors of matrix W_1 and W_2, respectively, and their elements are denoted by $w_{1_{sf}}$ et $w_{2_{if}}$.

Within the framework of the classical Matrix Factorization technique, the model parameters W_1 and W_2 can be learned by optimizing the objective function (2) using the Stochastic Gradient Descent (SGD) method.

$$O^{MF} = \sum_{(s,i)\in R} \left(R_{si} - w_{1_s} w_{2_i}^T \right)^2 + \lambda \left(\| W_1 \|_F^2 + \| W_2 \|_F^2 \right) \tag{2}$$

In this equation, $\| \; . \; \|_F^2$ is the Frobenius norm, and λ is a regularization term used to avoid overfitting. The quantity $R_{si} - w_{1_s} w_{2_i}^T$ represents the prediction error e_{si} for a couple (*student, task*). In the Weighted Multi-Relational Matrix Factorization approach (Thai-Nghe & Schmidt-Thieme, 2015), we consider a set $\{E_1, ..., E_N\}$ of N entity types connected by M types of relations $\{R_1, ..., R_M\}$ that can be strongly correlated to each other. In this case, the matrices factor latent, designating the model parameters, are given by: $W_1, W_2, ..., W_n \; (n \in N)$. Moreover, this approach suggests that some relationships carry more weight than others by imposing a weight factor θ. In this case, the objective function (2) becomes:

$$O^{WMRMF} = \sum_{r=1}^{M} \Theta_r \sum_{(s,i)\in R_r} \left(R_{r_{si}} - w_{r1_s} w_{r2_i}^T \right)^2 + \lambda \left(\sum_{n=1}^{N} \| W_n \|_F^2 \right) \tag{3}$$

In Equation 3, the weight function is defined as follows:

$$\Theta_r = \begin{cases} 1, & if \;\; r \; is \; the \; main \; relation \\ \theta, & if \;\; (0 < \theta < 1) \end{cases} \tag{4}$$

In this Equation 4, the value of θ is equal to 1 for the principal relation, and this value is included in the interval $\left]0;1\right[$ for the other relations, according to the degree of importance of these relations.

1.2.2. Weighted Multi-Relational Matrix Factorization and Social (So-WMRMF) approach

In the *So*-WMRMF approach proposed by Assielou et al. (2020a), it is assumed that a student's s performance is affected by their N_s work group friends in the following way:

$$\hat{w}_{1_s} = \frac{\sum_{u\in N_s} T_{s,u} w_{1_u}}{\sum_{u\in N_s} T_{s,u}} \tag{5}$$

In Equation 5, $\hat{w}_{1_s}$ denotes the estimated characteristic vector of student s, given those of their work group companions. T is a matrix in which each element $T_{s,u}$ represents the influence value of a student $u \in N_s$ on student s. In the *So*-WMRMF approach, the objective function (03) becomes:

$$O^{So-WMRMF} = O_{r=1}^{W} + O_{r\neq 1}^{W} \tag{6}$$

In Equation 6, the functions $O_{r=1}^{W}$ and $O_{r\neq 1}^{W}$ are given by Equations 7 and 8, respectively:

$$O_{r=1}^{W} = \Theta_r \sum_{(s,i)\in R} \left(R_{si} - \hat{w}_{1_s} w_{2_i}^T \right)^2 + \lambda \left(\| W_1 \|_F^2 + \| W_2 \|_F^2 \right) + \lambda_T \sum_{s=1}^{S} \left(w_{1_s} - \frac{\sum_{u\in N_s} T_{s,u} w_{1_u}}{\sum_{u\in N_s} T_{s,u}} \right)^2 \tag{7}$$

$$O_{r\neq 1}^{W} = \sum_{r=2}^{M} \Theta_r \sum_{(s,i)\in R_r} \left(R_{r_{si}} - w_{r1_s} w_{r2_i}^T \right)^2 + \lambda \left(\sum_{n=1}^{N} \| W_n \|_F^2 \right) \tag{8}$$

The *So*-WMRMF model updates these parameters $W_1, W_2, ..., W_n$ using the Stochastic Gradient Descent method via Equations 9 and 10:

$$w'_{r1_{sk}} = \begin{cases} w_{r1_{sk}} + \beta\left(2\Theta_r e_{si} w_{r2_{ik}} - \lambda w_{r1_{sk}}\right) + \lambda_T\left(X+Y\right), \text{ if } r=1 \\ w_{r1_{sk}} + \beta\left(2\Theta_r e_{r_{si}} w_{r2_{ik}} - \lambda w_{r1_{sk}}\right), \text{ if } r \neq 1 \end{cases} \quad (09)$$

$$w'_{r2_{ik}} = w_{r2_{ik}} + \beta\left(2\Theta_r e_{r_{si}} w_{r1_{sk}} - \lambda w_{r2_{ik}}\right) \quad (10)$$

λ_T is a regularization term used to normalize the terms of Equation 9. The expressions of X and Y are given through Equations 11 and 12, respectively:

$$X = \left(\frac{T_{s,s}}{\sum_{u\in N_s} T_{s,u}} - 1\right)\left(w_{1_{sk}} - \frac{\sum_{u\in N_s}' T_{s,u} w_{1_{uk}}}{\sum_{u\in N_s} T_{s,u}}\right) \quad (11)$$

$$Y = \sum_{t\in N_S \backslash s} \frac{T_{t,s}}{\sum_{w\in N_t} T_{t,w}}\left(w_{1_{tk}} - \frac{\sum_{w\in N_t}' T_{t,w} w_{1_{wk}}}{\sum_{w\in N_t} T_{t,w}}\right) \quad (12)$$

1.2.3. Modelling of Emotional Influence ε_{si}

In the emotional impact modelling approach proposed by Assielou et al. (2020b), the authors adopt the principle that the performance of a student *s* depends not only on their intrinsic abilities but also on the impact of their experienced emotions. In this approach, emotions are assessed using the AEQ (Achievement Emotions Questionnaire) Self-Assessment Questionnaire proposed by Pekrun (2006). In Assielou et al. (2020b), ε_{si} is a Multiple Linear Regression model whose variables $e=\left(e_1,e_2,\ldots,e_8\right)^T$ are the intensities of the eight test emotions linked to the AEQ, see Table 1. The different coefficients of this model are the elements of $\alpha=\left(\alpha_1,\alpha_2,\ldots,\alpha_8\right)$.

Table-1. Model ε_{si} variables (Assielou et al. 2020b) description.

Variables	e_1	e_2	e_3	e_4	e_5	e_6	e_7	e_8
Intensity of :	Enjoyment	Hope	Pride	Relief	Anger	Anxiety	Shame	Hopelessness

ε_{si} designates the impact of emotions on the performance of student *s* when completing task *i* and is developed using data collected during the AEQ survey. It is defined as in Equation 13:

$$\varepsilon = \alpha . e + \alpha_0 \quad (13)$$

2. Materials and Methods

The approach proposed in this paper combines the two models *So*-WMRMF and ε_{si} as defined in the previous section. This section describes the methodology used.

2.1. Problem Formulation

This approach associates a performance score as well as any emotions felt by the student when performing the task. We also combine the skills learned by the student and establish a link between the tasks to be performed and the various skills in the field. Figure 1 illustrates the five types of domain relations exploited by our approach.

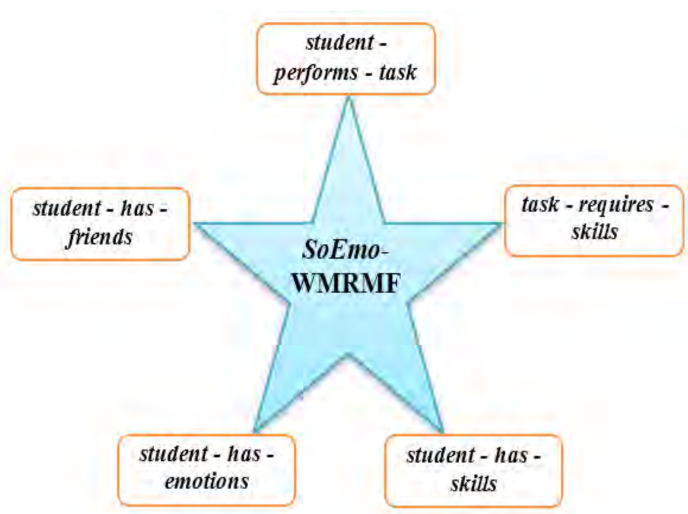


Figure-1. Relationships taken into account in the *SoEmo*-WMRMF approach.

The approach takes into account the fact that a student may experience, at a specific time, not a single emotion but rather a combination of several achievement emotions related to the test. This is the case, for example, when a student feels both anxious and desperate. Therefore, the challenge for us is to create a way for ITS to manage a combination of emotions in order to enhance students' learning experience.

Table-2. SoEmo-WMRMF Training algorithm

Algorithm : *SoEmo*-WMRMF Training

Input

N *: number of entities ;* M *: number of relations ;* F *: number of latent factors ;* R_r *: for each relations (from Step (1)) ;* θ *: weight ;* λ *: regulation term ;* λ_T *: regulation term;* β *: learning rate ;* K *: Latent factors ;* T *: Matrix factors ;* α_1 , α_2 , α_3 , α_4 , α_5 , α_6 , α_7 , α_8 *: respectively emotions Enjoyment, Hope, Pride, Relief, Anger, Anxiety, Shame and Hopelessness factors.*

Output

$\{W_j\}_{j=1...N}$ *: latent factor matrices for each entity j*

Initialize W_j *for each of the* N *entities using* $N(\mu, \sigma^2)$
Initialize Θ_r *for each of the* M *relations*
Initialize matrix T via step (2)
Initialize matrix ε via step (3)
While (Stopping criterion is not met) do
  for each relation $R_r = \{(E_{1r}; E_{2r})\}$ *in* $\{E_1, ..., E_M\}$ *do*
    for $s = 0$ to number of rows-1 of R_r *do*
      for $i = 0$ to number of rows-1 of R_r *do*
        $e_{si} = R_{si} - \hat{p}_{si}$
        for $k = 0$ to K-1 *do*
          $infs = T_{s,s}$
          if $r = 1$ *do*
            for $n = 1$ *to* N_s *do*
              $infnx = infnx + T_{s,n}$
              $X = X + T_{s,u} \times W_1[s][k]$
            end for
            $X = (infs / infnx - 1)(W_1[s][k] - X / infnx)$
            for $t = 1$ *to* $N_S \setminus s$ *do*
              for $w = 1$ *to* N_s *do*
                $infny = infny + T_{t,w}$
                $Y_1 = Y_1 + T_{t,w} \times W_1[w][k]$
              end for
              $Y = Y + (T_{t,s} / infny)(w_{1_{sk}} - Y_1 / infny)$
            end for
            Update $w_{r1_{sk}}$ using equation (09) *for* $r = 1$
          else
            Update $w_{r1_{sk}}$ using equation (09) *for* $r \neq 1$
          end if
        end for
        Update $w_{r2_{ik}}$ using equation (10)
      end for
    end for
  end for
end while
Return $\{W_j\}_{j=1...N}$

2.2. Methodology

Since the challenge of using models based on the Matrix Factorization technique is to find the optimal parameters $W_1, W_2, ..., W_n$, we have adopted the methodology below, comprising four steps:

- Step 1: The first step is to extract from all the learning data the performance matrix, the matrix of student outcomes by skills and the expert's matrix. These different matrices are taken from the field of study. As part of this contribution, we worked on a dataset described in section 2.3.
- Step 2: The second step is based mainly on the student performance matrix extracted from step 1. It calculates for each student the average performance on all the performed tasks and normalizes this value in the interval $]0;0,5]$. This obtained value is used as the weight or influence factor of a student in a given group. The set of its values allows us to generate the matrix of mutual influence $T \in \mathbb{R}^{S \times S}$ in which T_{su} for example, is the value of the influence of the student $u \in N_s$ (N_s being the set of the group mates of student s) on student *s*.
- Step 3: The third step consists in calculating as a function of the emotions felt and their intensity $e_1, e_2, ..., e_8$, the emotional impact ε_{si} on the performance of student *s* when carrying out task *i*, as described by Equation 13. Together, all its values allow us to generate the matrix of emotional impacts $\varepsilon \in \mathbb{R}^{S \times I}$. The intensities of the emotional scales are obtained through the AEQ questionnaire, which uses a 5-point Likert scale for ratings.
- Step 4: The fourth step consists in optimizing the choice of the parameters $W_1, W_2, ..., W_n$ (In this application framework, $n = 5$ for the 5-relation type) by using the *SoEmo*-WMRMF algorithm below. This algorithm proceeds by first initializing the model parameters from the normal distribution $N(\mu, \sigma^2)$, taking the expectation $\mu = 0$ and the standard deviation $\sigma = 0.01$.

Numerical simulation performed using the *SoEmo*-WMRMF algorithm not only determines the model parameters but also the optimal values of matrix $\alpha = (\alpha_1, \alpha_2, \ldots, \alpha_8)^T$ parameters.

2.3. Data Set for Machine Learning

To assess our prediction approach using socio-emotional attributes, we conducted a survey of 250 students enrolled in their final year at a general secondary school in Daloa (Côte d'Ivoire). The sample consisted of 80 girls with an average age of 16 and 170 boys with an average age of 17. The AEQ questionnaire was filled out several times during different evaluations to avoid the problem of "*subject emotion*", i.e., the student feeling specific emotions depending on the subject in which they were being assessed. In addition to the questionnaire on emotions, we also identified the practical organization of the previously formed study groups. The majority of groups are maded up of two or three students, the numbers of which are shown in Table 3. From this data sample, we extracted five (5) matrices. The first relates to the "*student-performs-task*" relationship, the second to the "*student-has-skills*" relationship, the third to the "*task-requires-skills*" relationship, the fourth to "*student-has-friends*" and the fifth to the "*student-has-emotions*" relationship.

Table-3. Composition of groups.

	Number of groups	Number of students
Groups of 2 students	40	140
Groups of 3 students	20	
students not belonging to any group		110
Total number of students		250

We also present the percentage composition of the different groups in our data set. Of the 250 students, 44% are not part of a working group, see Figure 2.

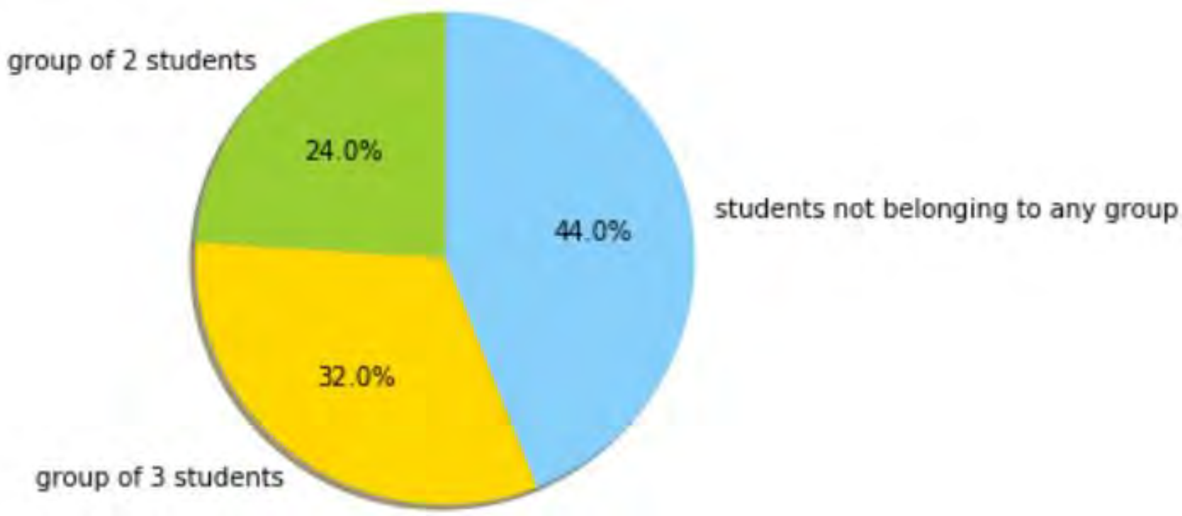


Figure-2. Distribution of students by work group.

To avoid the problem of overfitting, we used the Cross-Validation (CV) technique. To this end, we divided our sample into two subsets, i.e., 5/6 for machine learning and 1/6 for the test phase. We evaluated this approach under the same conditions as those used in Assielou et al. (2020b), taking into account the same simulation environment. To compare the performance of our approach and that of the alternative state-of-the-art approaches, we used the Root Mean Squared Error (RMSE) metric, provided in Equation 14 below:

$$RMSE = \sqrt{\frac{1}{|D^{test}|} \sum_{(s,i)\in D^{test}} \left(p_{si} - \hat{p}_{si}\right)^2} \qquad (14)$$

For the sake of fairness in the comparison, we initialized the parameters $\{W_j\}_{j=1\ldots N}$ from the same range of random values for all the approaches. The relevant parameters of each model have been carefully adjusted to achieve the best possible performance. Table 4 gives the different values of the parameters used to optimize the different models simulated in the same experimental environment.

Table-4. Optimization parameters.

Models	Parameters
WMRMF	$K=2$; #iter=320 ; $\beta = 3.10^{-3}$; $\lambda = 75.10^{-3}$; $\theta \in \{1.0;0.80;0.70\}$
So-WMRMF	$K=2$; #iter=320 ; $\beta = 3.10^{-3}$; $\lambda = 75.10^{-3}$; $\lambda_T = 75.10^{-5}$; $\theta \in \{1.0;0.60;0.70\}$
Emo-WMRMF	$K=2$; #iter=320 ; $\beta = 3.10^{-3}$; $\lambda = 15.10^{-4}$; $\theta \in \{1.0;0.40;0.80;0.70\}$; $\alpha_1 = 2.10^{-3}$; $\alpha_2 = 2.10^{-3}$; $\alpha_3 = -3.10^{-3}$; $\alpha_0 = 0$
SoEmo-WMRMF	$K=2$; #iter=320 ; $\beta = 5.10^{-3}$; $\lambda = 5.10^{-4}$ $\lambda_T = 25.10^{-5}$; $\theta \in \{1.0;0.40;0.80;0.70\}$; $\alpha_1 = 2.10^{-3}$; $\alpha_2 = 2.10^{-3}$; $\alpha_6 = -3.10^{-3}$; $\alpha_0 = 0$

3. Results and Discussion

In this section, we present the results of our approach, and we discuss these results in parallel with those of the previously proposed models. The results in Figure 3 show that, with regard to our dataset, the *SoEmo*-WMRMF model improves the RMSE error compared to *So*-WMRMF and *Emo*-WMRMF models.

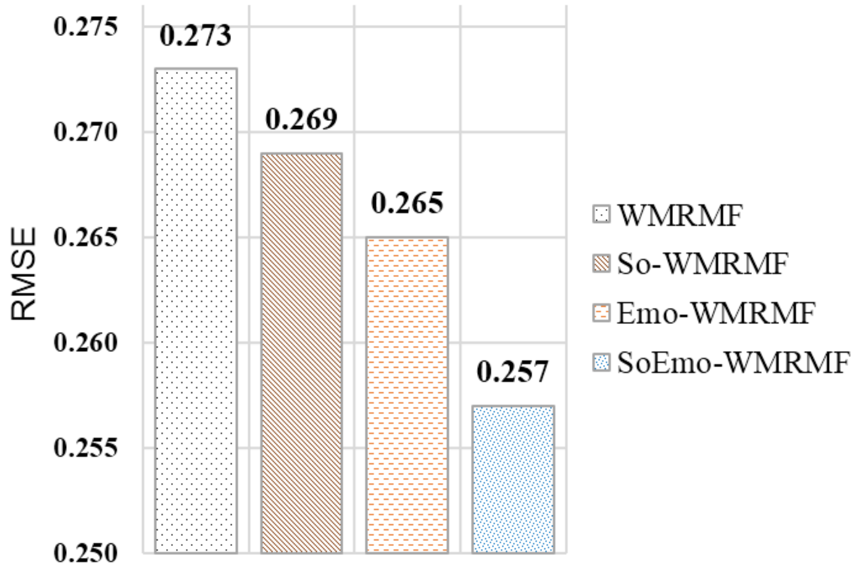


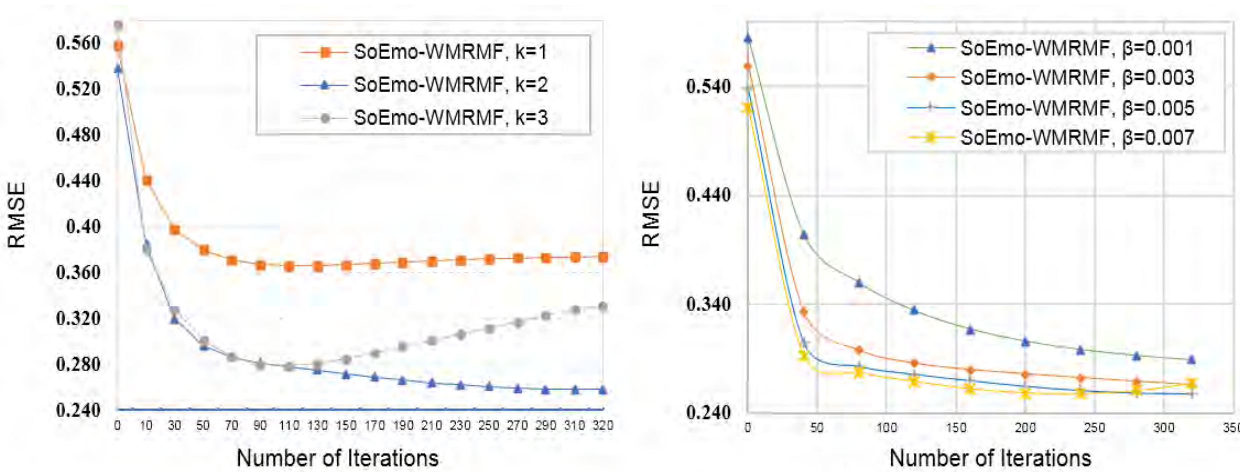
Figure-3. RMSE results on our data set.

Note that the *Emo*-WMRMF model significantly improves the RMSE error compared to the *So*-WMRMF model. The choice of emotion as an attribute in the domain for predicting performance thus appears advantageous over the choice of mutual influence factors in the context of friendly group relations. The results obtained from the *SoEmo*-WMRMF model show that taking into account both these socio-emotional attributes in performance prediction systems offers better prospects for computer learning systems. This result corroborates those of the authors Turi et al. (2020) and Nasir and Masrur (2010) who have shown, in empirical studies, that socio-emotional intelligence is a predictor of academic performance and a prerequisite for academic achievement.

Table-5. Comparison of different approaches.

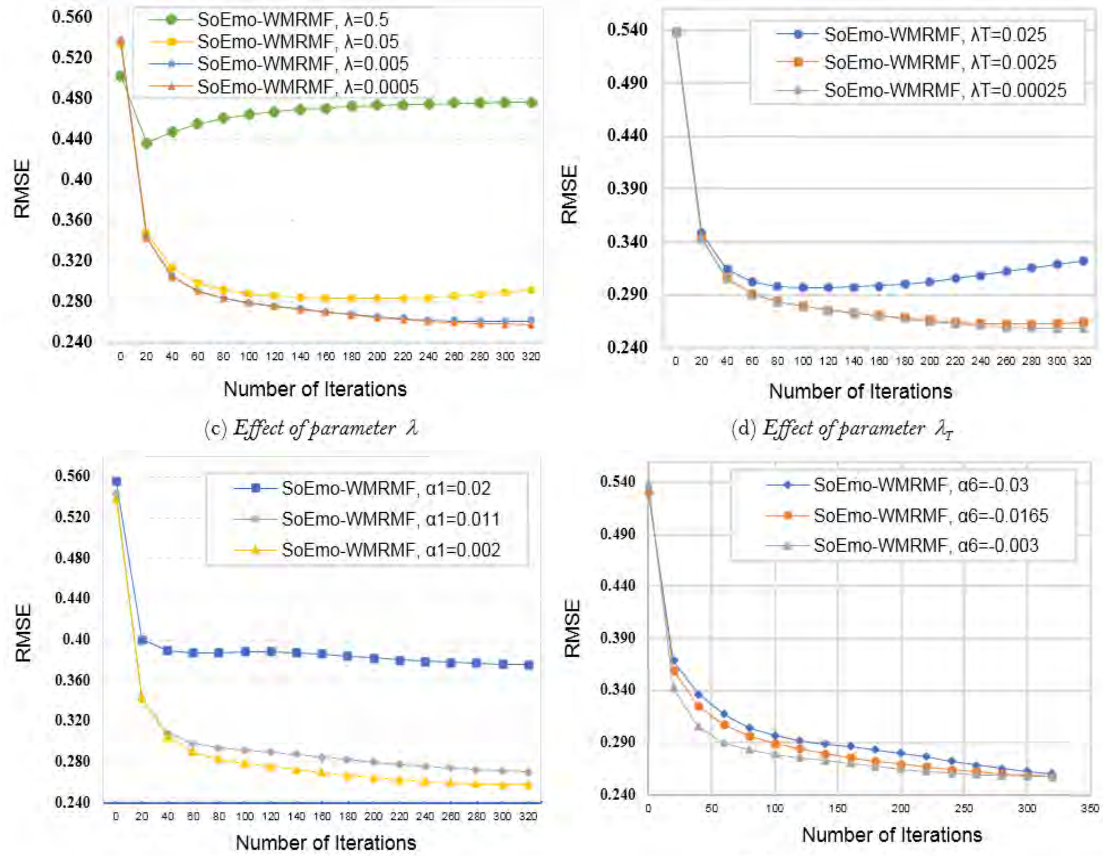
	RMSE results
Global Average	0.436
Item Average	0.421
User Average	0.296
MF	0.286
MRMF	0.283
WMRMF	0.273
So-WMRMF	0.269
Emo-WMRMF	0.265
SoEmo-WMRMF	0.257

We also compared the *SoEmo*-WMRMF model to several other approaches, including MRMF, MF, User Average, Item Average and Global Average, by ranking them in order of precision in terms of performance prediction (see Table 5). Since the *SoEmo*-WMRMF approach uses several parameters, we have simulated in parallel the effects of some of these parameters: K , β , λ , λ_T , α_1, α_2 , α_6 on its performance. To carry out this evaluation, we investigated the role of each of the parameters by varying each one in turn and recording the results. Figure 4 shows the results of this investigation.



(a) *Effect of parameter K*

(b) *Effect of parameter β*



(c) *Effect of parameter* λ (d) *Effect of parameter* λ_T

(e) *Effect of parameter* α_1 (f) *Effect of parameter* α_6

Figure-4. Effect of parameters K , β , λ , λ_T , α_1 , α_6 on *SoEmo*-WMRMF model performance.

From Figure 4 (a), we observe that the values of the latent factor $K=1$ and $K=2$ give a good evolution of the model in terms of progressive reduction of the prediction error. However, for a value of $K=2$, the system is more accurate. For $K=3$ the model becomes less efficient from an iteration value greater than 100. The values of the learning rate $\beta=0.005$ and $\beta=0.007$ prove to be more appropriate for our data set (see Figure 4 (b)) for iteration values belonging to the interval $\left]0;240\right]$. However, the model experiences an overfitting phenomenon beyond an iteration of 240 for $\beta=0.007$. To solve this problem, the ideal value for the learning rate is $\beta=0.005$. The proposed approach progressively gains in performance when the parameter λ changes from 0.5 to 0.0005 (see Figure 4 (c)). The performance of the *SoEmo*-WMRMF model (see Figure 4 (d)) gradually improves and tends to be stable when the regulation rate λ_T decreases from 0.025 to 0.00025. This rate makes it possible to regulate or adjust the effect of the performance between students belonging to the same work group. This parameter is used to standardize the new terms (taking into account the different characteristics of group mates) of the objective function (7). The optimum value of parameter λ_T for a good fit is around 25.10^{-5}. The parameters $(\alpha_1,\alpha_2,...,\alpha_8)$ are the multiplicative coefficients of the intensities of the different emotional scales linked to the test (see section 2.2.2). In particular, α_1 and α_6 respectively define the weight of the two scales of enjoyment and anxiety in our data set derived from the AEQ questionnaire. Enjoyment is categorized as positive valence emotion while anxiety is categorized as negative valence emotion. The optimal values of α_1 and α_6 revolve around 0.002 and -0.003 respectively, obeying the valences of these emotional scales as described by Pekrun (2006) control-value theory of achievement emotions.

4. Conclusion

In this paper, we have proposed a new approach to the prediction of student performance by taking into account not only students' cognitive abilities but also the impact of students' socio-emotional attributes in the learning environment. This approach takes advantage of the performance of the *So*-WMRMF model and the impact of emotions on student performance to refine the prediction results. To our knowledge, it is the first Matrix Factorization approach that exploits five types of domain relations: the first relates to the "*student-performs-task*" relationship, the second to the "*student-has-skills*" relationship, the third to the "*task-requires-skills*" relationship, the fourth to "*student-has-friends*" and the fifth to the "*student-has-emotions*" relationship. The evaluation that was carried out on a sample of data extracted from a survey carried out in a general secondary education institution showed that the *SoEmo*-WMRMF model provides a better performance in terms of reducing the RMSE error compared to other simulated models.

The performance prediction approach proposed in this paper only exploits positive social relationships between students. However, some students can also sometimes have negative social influences on others. This can induce more negative emotions than positive and have the consequence of demotivating them in the learning process. It would then be important to study the impact of these negative social relationships on the prediction of students' performances.

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