

Multi-Relational and Social-Influence Model for Predicting Student Performance in Intelligent Tutoring Systems (ITS)



Kouamé Abel Assielou, Cissé Théodore Haba, Tanon Lambert Kadjo, Kouakou Daniel Yao, Bi Tra Goore

Abstract: Recent studies have shown that Matrix Factorization (MF) method, deriving from recommendation systems, can predict student performance as part of Intelligent Tutoring Systems (ITS). In order to improve the accuracy of this method, we hypothesize that taking into account the mutual influence effect in the relations of student groups would be a major asset. This criterion, coupled with those of the different relationships between the students, the tasks and the skills, would thus be essential elements for a better performance prediction in order to make personalized recommendations in the ITS. This paper proposes an approach for Predicting Student Performance (PSP) that integrates not only friendship relationships such as workgroup relationships, but also mutual influence values into the Weighted Multi-Relational Matrix Factorization method. By applying the Root Mean Squared Error (RMSE) metric to our model, experimental results from KDD Challenge 2010 database show that this approach allows to refine student performance prediction accuracy.

Keywords : Matrix Factorization, Student Performance Prediction, Intelligent Tutoring System, Social-Influence, Recommender Systems.

I. INTRODUCTION

Intelligent Tutoring Systems development began in the 1970s with the goal to improve Computer-Assisted Learning

(CAL). STI-driven progress needed to be operationalized through the use of Artificial Intelligence (AI) methods to provide highly personalized feedback-based education tailored to the needs of the students. Their aim is to support learning by simulating the teaching skills and field expertise of human tutors and to produce the same kind of learning and flexibility between teachers and students [1]. An ITS is made up of three domains: Computer Science, Psychology and Education. Specifically, (i) artificial intelligence explains how to reason about intelligence and therefore about learning, (ii) psychology (cognitive science) explains how people think and learn, and (iii) education is about center on the best way to support teaching / learning [2]. Although, there are different Intelligent Tutorial Systems with different architectures, their basic architecture has four components (modules / models) that are (see Figure 1):

- a Domain-Model that defines the content to be taught;
- a Tutoring Model that defines how to teach;
- a Student-Model that can personalize the learning taking into account this one;
- an Interface-Model that defines the visible means allowing the interrelation between student and the system.

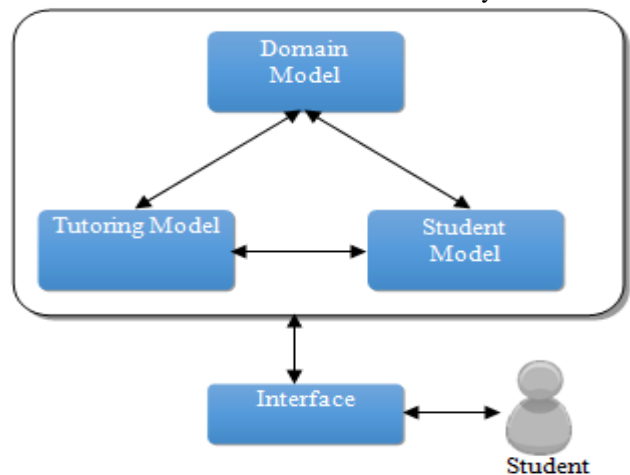


Fig. 1. Classic Intelligent Tutoring System architecture

The Student Model is an important component for more than one reason in any ITS. It can guide the interactions between the student and the system. Student modeling is used to represent student's knowledge evolution, to predict his / her performance for different skills over time [3] and to determine the next content to present to the student to give continuity to his learning [4].

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This modeling is also important for re-researchers as it provides them with practical information to make decisions about how to adapt the learning experience to student's needs. Thus, in order to determine the next content to be displayed and specially to adapt the learning, it is important for the current systems, to have a precision of the students' performances prediction. The prediction of student performance is therefore a relevant issue and a major asset for improving learning in all ITS.

In this contribution, we want to solve the PSP problem by proposing a weighted multi-relational matrix factorization model that takes advantage of student-workgroup relationships with the consideration of Student Individual Influence Effect. We seek to provide our model with significant data to improve the accuracy of student performance predicting.

The organization of our paper is as follows: Section 2 provides the state-of-the-art techniques used for predicting student performance. Section 3 presents, in turn, the classical matrix factorization techniques while section 4 describes our multi-relational approach to predict student performance. Section 5 presents an evaluation of this approach and discusses our results with those of the state-of-the-art. Section 6 concludes the paper.

II. STATE-OF-THE-ART AND RELATED WORK

Personalized learning has the potential to improve learning process and overall learning outcomes [5][6]. This customization can be achieved through learning content adaptation and the application of an individualized learning strategy. Therefore, it is important for current ITS to have not only relevant information about students but also to predict their performance at each stage of their learning.

In the associated scientific literature, there is a wide variety of work related to Student Performance Predicting. Most of them are based on traditional methods such as Knowledge Tracing (KT) [7], linear regression [8], logistic regression [9], k-NN algorithms [10], support vector machines [11][12][13][14], decision trees [15][16], neural networks [17][18].

Recently, some authors such as Thai-Nghe and *al.*, [19][20] proposed to use techniques from the recommendation systems, in this case the Matrix Factorization (MF), for student performance prediction. The PSP problem could be considered as that of the prediction of an evaluation. From this perspective, the student, the task and the performance would become the user, the article and the evaluation respectively as presented in the classical recommendation systems. These researchers showed that the use of this technique could improve prediction results over regression methods by relying on past student performance. Other works like those done in [21] have shown that the MF method can be applied to students' raw scores by taking into account the notes in an interval of 0 and 100 instead of 0 and 1 as the work done in the literature. In [22][23], the authors proposed to improve this method by integrating the temporal effect as the students' knowledge improves over time. Experimental results show that the proposed approaches are promising. However, these works considered only one relation: that existing between the student and the task to be realized. To extend the predictive efficiency of this method, the authors Thai-Nghe and *al.*, [24] proposed to explore multiple relationships that may exist between students, tasks and their

metadata using Multi-Relational Matrix Factorization model (MRMF). They also propose a Weighted Multi-Relational Matrix Factorization (WMRMF) model to take into account the main relationship that contains the target variable. The authors Nedungadi et *al.*, [25] propose, in addition to the Multi-Relational factor, to integrate the student's bias, which is defined by the probability that a student performs task and task's bias that can reflect the degree of difficulty of the task. However, these methods have not benefited from social relationships that can be integrated. They ignored significant connections between students (registered in workgroups, for example), which is not in line with real-world observations. It has been shown, in fact, that group work promotes collaboration among students to achieve common learning goals and increases their performance, perseverance, and attitudes [26][27].

With the advent of social networks, social networking approaches to online referral are growing. These approaches, such as those proposed in [28][29][30], assume the existence of a social network among the users to make recommendations to a user on the basis of the evaluations of users having direct or indirect social relations with the given user. In [31], the authors Thanh-Nhan and *al.*, Propose precisely an approach to integrate the social relations of the users / students (for example, a friend of class) in the classic MF. The results show that this approach makes it possible to take advantage of student-to-model relationships and thereby improve forecasting results. However, this approach does not exploit the individual influence factor of group members. It does not exploit the different relationships between students, tasks and their metadata either.

In order to extend the functions of existing systems, Lukassenko [6] aims to define a complete content of a student model that can be taken into account by the intelligent and adaptive functions of knowledge assessment systems and learning. This empirical model contains categories of information such as: contact information, learning style, student current state (mood, mental state, physiological state) current level of knowledge and skills, objectives, learning progress, learning material used, user interface configuration... This point of view is shared by the authors Bicans and *al.*, [32] who propose the automatic addition of students learning style in the computer learning systems in general.

In this paper, we propose MRMF and WMRMF approaches that aggregate not only friendships with integration of the influence effect, but also relationships between students, tasks, and their metadata, so improve the accuracy of PSP in ITS.

III. MATRIX FACTORIZATION APPROACHES

A. Classical Matrix Factorization (MF) method

Let S denote a set of students, I a set of tasks and P a range of possible performance scores. According to the literature of recommendation systems models [33][25], the "student-performs-task" matrix R , considering a single attribute, Can be approximated by a product of two small matrices W_1 (student) and W_2 (task). Let $R \approx W_1 W_2^T$, as illustrated in Figure 2.



In this relation, $W_1 \in \mathbb{R}^{S \times F}$ is a matrix where each line s is a vector containing the F latent factors describing the student s and $W_2 \in \mathbb{R}^{T \times F}$ is a matrix where each line i is a vector containing the F factors latent describing the task i . Let w_{1_s} and w_{2_i} be the respective vectors of the matrices W_1 and W_2 such that their elements are designated by $w_{1_{sf}}$ and $w_{2_{if}}$.

A student s performance for a task i in the framework of MF technique can be predicted by:

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

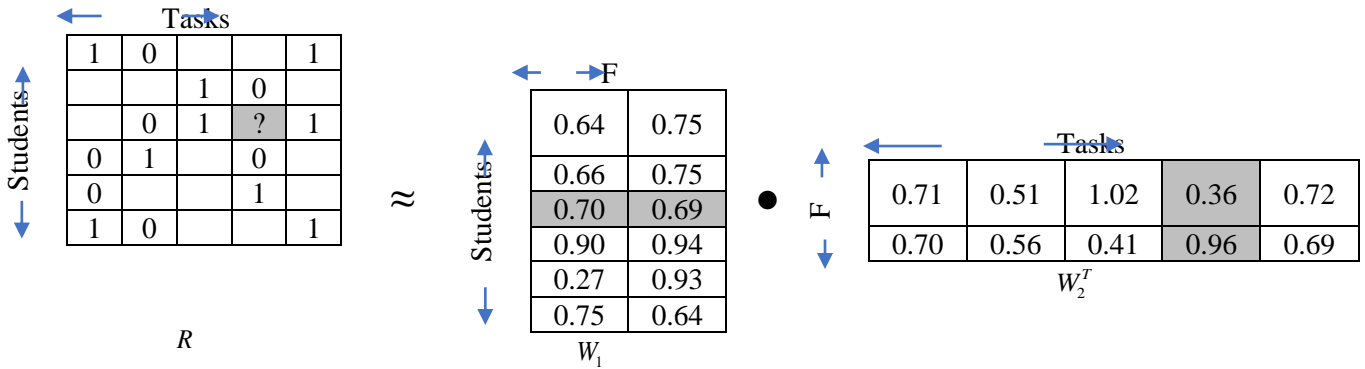


Fig. 2. Example of matrix factorization for the « student-perform-task » relation.

\hat{p}_{si} is the predicted performance value. W_1 and W_2 are the model parameters (latent factor matrices) or factor matrices. These matrices can be learned by optimizing the objective function (2) from a criterion, such as Root Mean Square Error (RMSE), using the stochastic gradient descent method as suggested in [34].

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

With $\|\cdot\|_F$ being the Frobenius standard; $\lambda(0 \leq \lambda < 1)$ is a regularization term used to avoid over-adjustments. In other words, λ is a parameter that make a compromise between the approximation error and the Frobenius norm of the model [33]. Let e_{si} denote the difference between the real performance value and the predicted performance value for each couple (student, task):

$$e_{si} = (R_{si} - w_{1_s} w_{2_i}^T) \quad (3)$$

R_{si} represents the real value of the student's performance for task i .

B. Multi-Relational Matrix Factorization Method (MRMF)

The MF model refers to a single type of unique relationship linking two types of entities. Let us consider a set $\{E_1, \dots, E_N\}$ of N types of entities connected by M types of relations $\{R_1, \dots, R_M\}$ which can be strongly correlated with each other. Let $W_1, W_2, \dots, W_n (n \in N)$ be the latent factor matrices (designating the model parameters) of each of the entity types. These latent factors describe the entity and are constructed by considering each relationship to which the

entity is associated. Taking into account the several relations of the domain, the objective function is given by [35] [24] [36]:

$$O^{MRMF} = \sum_{r=1}^M \sum_{(s,i) \in R_r} (R_{r,si} - w_{r1_s} w_{r2_i}^T)^2 + \lambda \left(\sum_{n=1}^N \|W_n\|_F^2 \right) \quad (4)$$

With $R_r = \{(E_{1_r}; E_{2_r})\} (r = 1 \dots M)$.

When learning model parameters, each factor matrix is updated according to all the relationship types it implies until a common convergence is reached [8] or the maximum number of pre-defined iterations is achieved.

C. Weighted Multi-Relational Matrix Factorization method (WMRMF)

Assuming some relationships have more weight compared to others, a θ weight factor is added to the MRMF model. The objective function thus becomes [24] [36] [37]:

$$O^{WMRMF} = \sum_{r=1}^M \Theta_r \sum_{(s,i) \in R_r} (R_{r,si} - w_{r1_s} w_{r2_i}^T)^2 + \lambda \left(\sum_{n=1}^N \|W_n\|_F^2 \right) \quad (5)$$

The weight function may be defined as follows:

$$\Theta_r = \begin{cases} 1, & \text{if } r \text{ is the main relationship} \\ \theta, & \text{if } (0 < \theta < 1) \end{cases} \quad (6)$$

For the learning process, the WMRMF model updates its latent factors using equations (7) and (9):

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$$w'_{r_{1,ik}} = w_{r_{1,ik}} - \beta \left(\frac{\partial O}{\partial w_{r_{1,ik}}} \right) \quad (7)$$

$$w'_{r_{2,ik}} = w_{r_{2,ik}} - \beta \left(\frac{\partial O}{\partial w_{r_{2,ik}}} \right) \quad (8)$$

With β that is the learning rate. By determining the gradients $\frac{\partial O}{\partial w_{r_{1,ik}}}$ and $\frac{\partial O}{\partial w_{r_{2,ik}}}$, we finally obtain:

$$w'_{r_{1,ik}} = w_{r_{1,ik}} + \beta (2\Theta_r e_{r_{si}} w_{r_{2,ik}} - \lambda w_{r_{1,ik}}) \quad (9)$$

$$w'_{r_{2,ik}} = w_{r_{2,ik}} + \beta (2\Theta_r e_{r_{si}} w_{r_{1,ik}} - \lambda w_{r_{2,ik}}) \quad (10)$$

IV. PROPOSED APPROACH

We propose a multi-relational factorization approach that can integrate not only friendship relationships such as

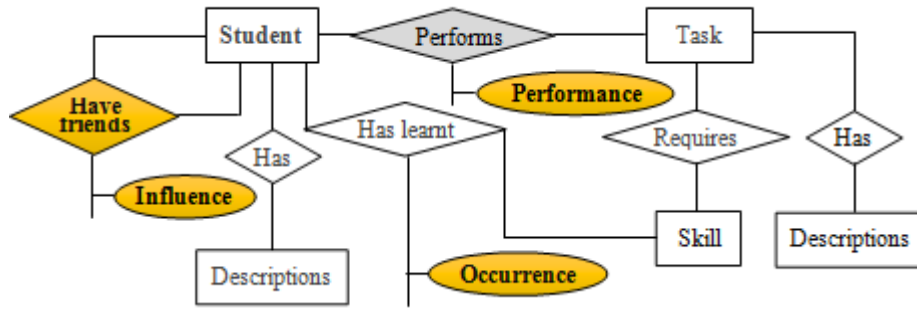
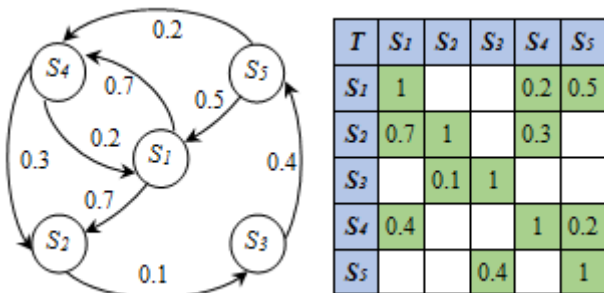


Fig. 3. Entity-association diagram for student performance prediction

B. Relationship matrix with social influence effect

In addition to the different relationships previously explored, our approach combines student friendly relationships such as workgroup relationships. The friendship network can essentially be modeled using a confidence graph of Figure 4 (a) or using a confidence matrix as shown in Figure 4 (b). In the confidence graph shown in Figure 4(a), 5 students (nodes, from S_1 to S_5) are connected to each other at 8 relationships (edges), and each relation is associated with a weight $T_{s,u}$ (influence value) in interval] 0;1]. $T_{s,u}$ is the influence value of student $u \in N_s$ (N_s being all student s friends) on student s . Thus, the influence value of the student S_4 on student S_1 is equal to 0.2 while that of the student S_5 on the student S_1 is equal to 0.5. For S_2 , S_1 has more influence on his learning than S_4 .



workgroup relationships, but also mutual influence values. The proposed methods are named So-MRMF (Multi-Relational Matrix Factorization and Social) and So-WRMF (Weighted Multi-Relational Matrix Factorization and Social)

A. Problem formulation

Our approach is essentially based on the work done in [31]. We propose a multi-relational approach integrating workgroup relationships. In this approach, we consider the relationship « *student-performs-task* » as the main relationship. Figure 3 presents in the form of entity-association diagram, the information that we take into account in our model. At the completion of a task by the student, we associate a performance score and the number of indices requested by the student. To properly solve task, the student must know specific skills, and the task itself is also associated with the skills to be learned by the student. "Occurrence" attribute gives the number of times the student has learned the skill.

Fig. 4. Example of trust relationships

Unlike the work done in [31], our matrix T is not binary; the value $T_{s,n}$ has rather a social influence effect belonging to the interval]0 ;1]. The value 1 corresponds to the influence $T_{s,s}$ that a student s has on himself. We hypothesize that the student has more impact on their own learning process than others have on him. This value taken is equal to 1. An influence value $T_{s,n} = 0$ means that there is no relationship of friendship between the student s and the student n .

By integrating the fact that the behavior of a student s is affected by his direct neighbors [31][38], likewise, s characteristic vector depends on the characteristic vectors of its direct neighbors. This formulation is given by:

$$\hat{w}_{1_s} = \frac{\sum_{u \in N_s} T_{s,u} w_{1_u}}{\sum_{u \in N_s} T_{s,u}} \quad (11)$$

Where \hat{w}_{1_s} is the estimated characteristic vector (latent factor vectors) of student s , given the characteristic vectors of his direct neighbors. The graphical model of Figure 5 is an example representing the integration of the confidence matrix through latent factor matrix W .

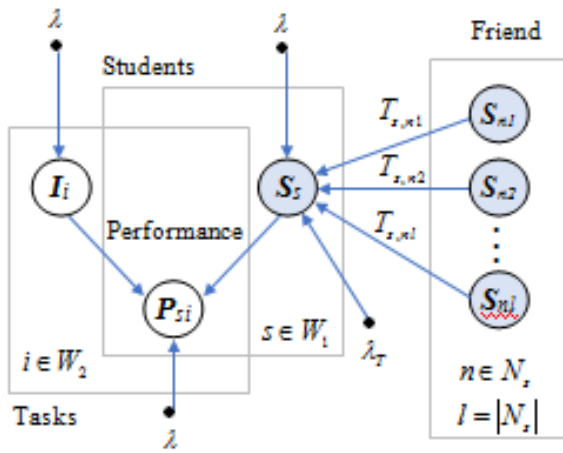


Fig. 5. Graphic model of performance prediction technique with social influence

λ_T is a regularization term (regularization weight) that will be added to normalize objective function terms. By replacing w_{1_s} by \hat{w}_{1_s} in equation (1), for predicting student s performance, we obtain:

$$\hat{p}_{si} = \sum_{f=1}^F \hat{w}_{1_{sf}} w_{2_{if}}^T = \hat{w}_{1_s} w_{2_i}^T \quad (12)$$

C. Multi-Relational Matrix Factorization and Social-influence approach (So-MRMF)

Taking into account the estimated characteristic vector of student s , the objective function expressed in equation (2) becomes:

$$O^{So-MF} = \sum_{(s,i) \in R} (R_{si} - w_{1_s} w_{2_i}^T)^2 + \lambda (\|W_1\|_F^2 + \|W_2\|_F^2) + \lambda_T \sum_{s=1}^S \left(w_{1_s} - \frac{\sum_{u \in N_s} T_{s,u} w_{1_u}}{\sum_{u \in N_s} T_{s,u}} \right)^2 \quad (13)$$

In this case, our multi-relational and social objective function is given by expression:

$$O^{So-MRMF} = O_{r=1} + O_{r \neq 1} \quad (14)$$

So that functions $O_{r=1}$ and $O_{r \neq 1}$ are given by the equations (15) and (16)

$$O_{r=1} = \sum_{(s,i) \in R} (R_{si} - \hat{w}_{1_s} w_{2_i}^T)^2 + \lambda (\|W_1\|_F^2 + \|W_2\|_F^2) + \lambda_T \sum_{s=1}^S \left(w_{1_s} - \frac{\sum_{u \in N_s} T_{s,u} w_{1_u}}{\sum_{u \in N_s} T_{s,u}} \right)^2 \quad (15)$$

$$O_{r \neq 1} = \sum_{r=2}^M \sum_{(s,i) \in R_r} (R_{r,si} - w_{r1_s} w_{r2_i}^T)^2 + \lambda \left(\sum_{n=1}^N \|W_n\|_F^2 \right) \quad (16)$$

It is assumed that $r=1$ denotes the main relationship taking into account the entities "student" and "task". The objective function $O_{r=1}$ is thus defined for the value $r=1$. The objective function $O_{r \neq 1}$, for its part, is defined for any other value of $r (r \neq 1)$. The objective function (14) is optimized by using stochastic gradient descent. Thus, our So-MRMF model updates its parameters by equations (17) and (18):

$$w'_{r1_{ik}} = \begin{cases} w_{r1_{ik}} + \beta (2e_{si} w_{r2_{ik}} - \lambda w_{r1_{ik}}) + \lambda_T (X + Y), & \text{if } r = 1 \\ w_{r1_{ik}} + \beta (2e_{r,si} w_{r2_{ik}} - \lambda w_{r1_{ik}}), & \text{if } r \neq 1 \end{cases} \quad (17)$$

$$w'_{r2_{ik}} = w_{r2_{ik}} + \beta (2e_{si} w_{r1_{ik}} - \lambda w_{r2_{ik}}) \quad (18)$$

X and Y expressions are given through equations (19) et (20)

$$X = \left(\frac{T_{s,s}}{\sum_{u \in N_s} T_{s,u}} - 1 \right) \left(w_{1_{sk}} - \frac{\sum_{u \in N_s} T_{s,u} w_{1_{uk}}}{\sum_{u \in N_s} T_{s,u}} \right) \quad (19)$$

$$Y = \sum_{t \in N_s \setminus s} \frac{T_{t,s}}{\sum_{w \in N_t} T_{t,w}} \left(w_{1_{tk}} - \frac{\sum_{w \in N_t} T_{t,w} w_{1_{wk}}}{\sum_{w \in N_t} T_{t,w}} \right) \quad (20)$$

Equations (19) and (20) have been proposed to give a reduced form of equation (17).

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

Considering the fact that some relations have more impact on the prediction than others, in weight term, the objective function of So-WMRMF model is given by:

$$O^{So-WMRMF} = O_{r=1}^W + O_{r \neq 1}^W \quad (21)$$

Such that the functions $O_{r=1}^W$ and $O_{r \neq 1}^W$ are given by the equations (22) and (23)

$$O_{r=1}^W = \Theta_r \sum_{(s,i) \in R} (R_{si} - \hat{w}_{1_s} w_{2_i}^T)^2 + \lambda (\|W_1\|_F^2 + \|W_2\|_F^2) +$$

$$\lambda_T \sum_{s=1}^S \left(w_{1_s} - \frac{\sum_{u \in N_s} T_{s,u} w_{1_u}}{\sum_{u \in N_s} T_{s,u}} \right)^2 \quad (22)$$



$$O_{r \neq 1}^W = \sum_{r=2}^M \Theta_r \sum_{(s,i) \in R_r} (R_{r,si} - w_{r1s} w_{r2i}^T)^2 + \lambda \left(\sum_{n=1}^N \|W_n\|_F^2 \right) \quad (23)$$

Our So-WMRMF model updates these parameters for each relationship via equations (24) and (25).

$$w'_{r1sk} = \begin{cases} w_{r1sk} + \beta(2\Theta_r e_{si} w_{r2ik} - \lambda w_{r1sk}) + \lambda_T (X + Y), & \text{if } r = 1 \\ w_{r1sk} + \beta(2\Theta_r e_{si} w_{r2ik} - \lambda w_{r1sk}), & \text{if } r \neq 1 \end{cases} \quad (24)$$

$$w'_{r2ik} = w_{r2ik} + \beta(2\Theta_r e_{si} w_{r1sk} - \lambda w_{r2ik}) \quad (25)$$

E. Learning phase: proposal of an algorithm for updating parameters.

The main issue of this technique is to find the optimal parameters W_1, W_2, \dots, W_n , we proposed the algorithm 1 (using a stochastic gradient descent) iterative below to update our model parameters. The algorithm 1 proposed for the model So-WMRMF proceeds by initializing the parameters from the normal distribution $N(\mu, \sigma^2)$, taking for expectation $\mu = 0$ and for standard deviation $\sigma = 0.01$.

Algorithm 1

Input

N : number of entities ; M : number of relations ; F : number of latent factors ; R_r : for each relations ; θ : weight ; λ : regulation term ; λ_T : regulation term ; β : learning rate ; K : Latent factors ; T : Matrix factors.

Output

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

1. Initialize W_j for each of the N entities using $N(\mu, \sigma^2)$
2. Initialize Θ_r for each of the M relations
3. **While** (Stopping criterion is not met) **do**
4. **for** each relation $R_r = \{(E_{1r}; E_{2r})\}$ in $\{E_1, \dots, E_M\}$ **do**
5. **for** $s = 0$ to number of rows-1 of R_r **do**
6. **for** $i = 0$ to number of rows-1 of R_r **do**
7. $e_{si} = R_{si} - \hat{p}_{si}$
8. **for** $k = 0$ to $K-1$ **do**
9. $infs = T_{s,s}$
10. **if** $r = 1$ **do**
11. **for** $n = 1$ to N_s **do**
12. $infnx = infnx + T_{s,n}$
13. $X = X + T_{s,u} \times W_1[s][k]$
14. **end for**
15. $X = (infs / infnx - 1)(W_1[s][k] - X / infnx)$
16. **for** $t = 1$ to $N_s \setminus s$ **do**
17. **for** $w = 1$ to N_s **do**
18. $infnv = infnv + T_{t,w}$
19. $Y_1 = Y_1 + T_{t,w} \times W_1[w][k]$
20. **end for**
21. $Y = Y + (T_{t,s} / infnv)(w_{1k} - Y_1 / infnv)$

22. **end for**
23. $W_1[s][k] \leftarrow W_1[s][k] + \beta(2\Theta_r e_{si} w_{r2ik} - \lambda w_{r1sk}) + \lambda_T (X + Y)$
24. **else**
25. $W_1[s][k] \leftarrow W_1[s][k] + \beta(2\Theta_r e_{si} w_{r2ik} - \lambda w_{r1sk})$
26. **end if**
27. **end for**
28. $W_2[i][k] \leftarrow W_2[i][k] + \beta(2\Theta_r e_{si} w_{r1sk} - \lambda w_{r2ik})$
29. **end for**
30. **end for**
31. **end for**
32. **end while**
33. **Return** $\{W_j\}_{j=1 \dots N}$

V. EVALUATION OF THE PROPOSED MODELS

A. Data Set

The data set for machine learning and testing comes from KDD Challenge 2010 (Knowledge Discovery Data) database. This database is the result of interaction records between students and computer-assisted tutoring systems. In the KDD Challenge 2010 datasets ie "Algebra", the problem is the central element of the interaction between students and the Tutoring System. Students solve problems in the tutor and each interaction between the student and the system is recorded as a transaction line. The information about students, tasks and skills in this database is shown in Table 1.

Table 1. Information of students, tasks and performances

Data set	#Student	#Task	#Skill	#Performance
Algebra 2008-2009	3,310	1,422,200	2,979	8,918,054

B. Evaluation

For our models' evaluation, we used the dataset "Algebra". Given the high data size of this database for our work environment, we reduced the sample for the evaluation. This sample is composed of:

- 247 students;
- 4000 tasks;
- 1664 skills;

In this sample, we extracted three (3) matrices. The first is related to the relationship "student-performs -tasks". This matrix is of dimension 247 x 4000. This matrix comprises 180676 known performances. We used two datasets: one for machine learning and one for testing. To perform cross validation, we used 9/10 performance for the machine learning phase and 1/10 for the prediction phase. The second matrix relates to "student-as learnt-skill" relationship and the third to "task-requires-skill" relationship. Since the learning base does not have student group relationships, we simulated two group formation scenarios in all of the 247 students used for experiment. For each of the two scenarios, 40 groups of 4 students are formed. 160 students belong to a group while 87 belong to no group.



In the scenario 1 noted *So1.*, The influence values between students are all set at 1. In the scenario 2 noted *So2.*, these values are a function of the performances obtained by each student in the group. The average yield of a member of the group is calculated, in the interval] 0;0.5], on the basis of the tasks performed. This yield is taken by default as the influence value of this member on the others. However, the influence value of a member of the group on itself is equal to 1.

C. Results

We implement So-MF, So-MRMF and So-WMRMF models taking into account three attributes (three relations) and the group relation as described in our association entity diagram. Our work environment is a 64-bit operating system computer, 4GB of ram, intel Core i3. Our model is designed in Python language.

To compare our approach with classical matrix factorization methods (MF, MRMF and WMRMF), we used the RMSE (Root Mean Squared Error) metric. This metric is calculated as follows :

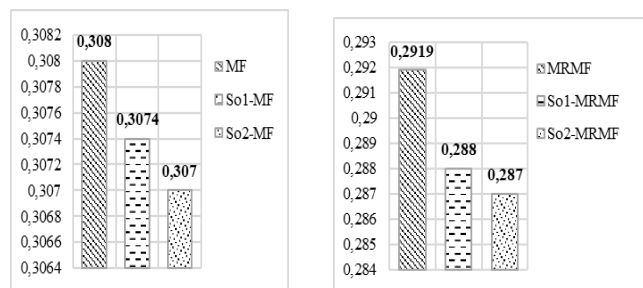
$$RMSE = \sqrt{\frac{\sum_{(r,s,i) \in D^{test}} (p_{si} - \hat{p}_{si})^2}{|D^{test}|}} \quad (26)$$

For this, the parameters used to optimize the model are contained in table 2.

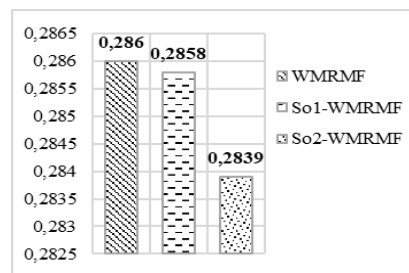
Table 2. Optimizing parameters

Methods	Parameter
<i>MF</i>	$K = 3 ; \#iter = 30 ; \beta = 2.10^{-3} ; \lambda = 55.10^{-5}$
<i>So1-MF ; So2-MF</i>	$K = 3 ; \#iter = 60 ; \beta = 2.10^{-3} ; \lambda = 15.10^{-5} ; \lambda_T = 15.10^{-5}$
<i>MRMF ; So1-MRMF ; So2-MRMF ;</i>	$K = 4 ; \#iter = 70 ; \beta = 2.10^{-3} ; \lambda = 55.10^{-5} ; \lambda_T = 55.10^{-5}$
<i>WMRMF ; So1-WMRMF ; So2-WMRMF ;</i>	$K = 4 ; \#iter = 80 ; \beta = 2.10^{-3} ; \lambda = 55.10^{-5} ; \lambda_T = 55.10^{-5} ; \theta \in \{0.85;0.80;0.70\}$

Figure 6 gives the results of the experiments carried out by applying the two scenarios described above to each of the MF, MRMF and WMRMF methods.



(a) RMSE with MF method (b) RMSE with MRMF method



(c) RMSE with WMRMF method

Fig. 6. RMSE results on Algebra data set using the two scenarios *So1* and *So2*

In Figure 6 (a), *So1-MF* and *So2-MF* models outperform the *MF* model. Figure 6 (b) shows that *So1-MRMF* and *So2-MRMF* models are significantly more accurate than the *MRMF* model. In Figure 6 (c), the *So1-WMRMF* model is significantly better compared to the *WRMF* model while the *So2-WMRMF* model greatly outperforms *WRMF* and *So1-WMRMF* models. Figure 7 gives a summary of RMSE metric for *So2-MF*, *So2-MRMF* and *So2-WMRMF* methods.

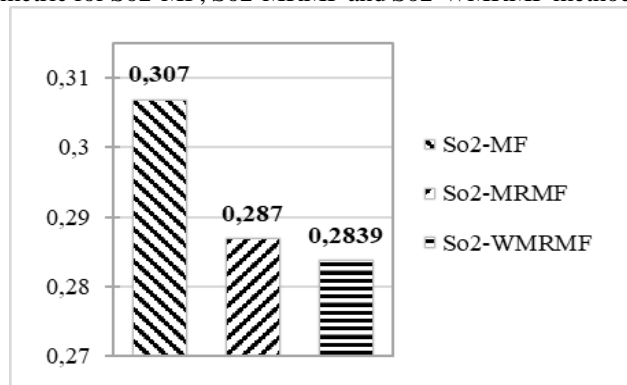


Fig. 7. RMSE results on Algebra data set using the two scenarios *So1* and *So2*

These results show that the *So2-WMRMF* model outperforms all other models. Taking into account the influence factor on Weighted Multi-Relational Matrix Factorization, in order to predict performance, gives not only a better accuracy of prediction on the performances, but also, that it presents better results compared to the methods of standard Matrix Factorization.

VI. CONCLUSION

In this paper, we have proposed a student performance prediction approach that integrates not only friendship relationships such as workgroup relationships, but also mutual influence values into Weighted Multi-Relational Matrix Factorization method. By applying RMSE metric to our models (*So2-MF*, *So2-MRMF*, *So2-WMRMF*), experimental results from the KDD Challenge 2010 database have shown that this approach can refine the accuracy of student performance prediction. The *So2-WMRMF* model outperforms all other models. In future work, the addition of some information such as the influence factor per student and per task and the definition of an influence value that takes advantage of real-life situations, would further improve the results of students' performances predictions in ITS.



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