ADAPTIVE CONTENT SEQUENCING WITHOUT DOMAIN INFORMATION

Carlotta Schatten[1] and Lars Schmidt-Thieme[1]
[1] *Information Systems and Machine Learning Lab, University of Hildesheim, Marienburger Platz 22, Hildesheim, Germany*
{*schatten, schmidt-thieme*}*@ismll.uni-hildesheim.de*

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Abstract: In Intelligent Tutoring Systems, adaptive sequencers can take past student performances into account to select the next task which best fits the student's learning needs. In order to do so, the system has to assess student skills and match them to the required skills and difficulties of available tasks. In this scenario two problems arise: (i) Tagging tasks with required skills and difficulties necessitate experts and thus is time-consuming, costly, and, especially for fine-grained skill levels, also potentially subjective. (ii) Learning adaptive sequencing models requires online experiments with real students, that have to be diligently ethically monitored. In this paper we address these two problems. First, we show that Matrix Factorization, as performance prediction model, can be employed to uncover unknown skill requirements and difficulties of tasks. It thus enables sequencing without explicit domain knowledge, exploiting the Vygotski concept of Zone of Proximal Development. In simulation experiments, this approach compares favorably to common domain informed sequencing strategies, making tagging tasks obsolete. Second, we propose a simulation model for synthetic learning processes, discuss its plausibility and show how it can be used to facilitate preliminary testing of sequencers before real students are involved.

1 INTRODUCTION

Intelligent Tutoring Systems (ITS) are more and more becoming of crucial importance in education. Apart from the possibility to practice any time, adaptivity and individualization are the main reasons for their widespread availability as app, web service and software. The system generally is composed of an internal user model and a sequencer, that, according to the given information, sequences the contents with a policy. On that side many efforts have been put into Bayesian Knowledge Tracing (BKT), starting with not personalized and single skills user modeling. The limit of this problem formulation became clear soon, also because the contents evolved together with the technology. Multiple skills contents were developed, e.g. multiple step exercises and simulated exploration environment for learning. In order to maintain the single skill formulation systems fell back on scaffolding, i.e. a built in structure was inserted in order to clearly distinguish within the content between the different steps/skills required. As a consequence, the engineering and authoring effort to develop an ITS increased exponentially obliging a meticulous analysis of the contents in order to subdivide and design them in clearly separable skills.

Other efforts have been put into adaptive sequencing. The main approach used can be reconnected to robotics, which has an availability of accurate simulators and tireless test subjects. The same cannot be said for ITS where, generally, apart from adults, also children of any age are involved.

In this paper we propose a novel method of sequencing based on Matrix Factorization Performance Prediction and Vygotski concept of Zone of Proximal Development. The main contributions are:

1. A content sequencer based on a performance prediction systems that (1) can be set up and preliminary evaluated in a laboratory, (2) models multiple skills and individualization without engineering/authoring effort, (3) adapts to each combination of contents, levels and skills available.

2. Simulated environment with multiple skill contents and students' knowledge representation, where knowledge and performance are modeled in a continuous way.

3. Experiments on different scenarios with direct comparison with informed baseline.

The paper is structured as follows: in Section 2 one can find a brief state of the art description, in Section 3 the explanation of the sequencer problem, in Section 4 the simulated learning process, in Section 5 the performance based policy and predictor, in Section 6 the experimental results and least the conclusions.

2 RELATED WORK

Many Machine Learning techniques have been used to ameliorate ITS, especially in order to extend learning potential for students and reduce engineering efforts for designing the ITS. The most used technology for sequencing is Reinforcement Learning (RL), which computes the best sequence trying to maximize a previously defined reward function. Both model–free and model–based (Malpani et al., 2011; Beck et al., 2000) RL were tested for content sequencing. Unfortunately, the model–based RL necessitates of a special kind of data sets called exploratory corpus. Available data sets are log files of ITS which have a fixed sequencing policy that teachers designed to grant learning. They explore a small part of the state–action space and yield to biased or limited information. For instance, since a novice student will never see an exercise of expert level, it is impossible to retrieve the probability of a novice student solving some contents. Without these probabilities the RL model cannot be built (Chi et al., 2011). Model–free RL, instead, assumes a high availability of students on which one can perform an on-line training. The model does not require an exploratory corpus but needs to be built while the users are playing with the designed system. Given the high cost of an experiment with humans, most authors exploit simulated single skill students based on different technologies like Artificial Neural Networks or self developed student models (Sarma and Ravindran, 2007; Malpani et al., 2011). Particularly similar to our approach is (Malpani et al., 2011), where contents are sequenced with a particular model–free RL based on the actor critic algorithm (Konda and Tsitsiklis, 2000), which was selected because of its faster convergence in comparison with the classic Q–Learning algorithm (Sutton and Barto, 1998). Unfortunately, RL algorithms still need many episodes to converge and will always need preliminary trainings on simulated students.
Our developed content sequencer is based on student performance predictions. An example of state of the art method is Bayesian Knowledge Tracing (BKT) and its extensions. The algorithm is built on a given prior knowledge of the students and a data set of binary student performances. It is assumed that there is a hidden state representing the knowledge of a student and an observed state given by the recorded performances. The model learned is composed by slip, guess, learning and not learning probability, which are then used to compute the predicted performances (Corbett and Anderson, 1994). In the BKT extensions also difficulty, multiple skill levels and personalization are taken into account separately (Wang and Heffernan, 2012; Pardos and Heffernan, 2010; Pardos and Heffernan, 2011; D Baker et al., 2008). BKT researchers have discussed the problem of sequencing both in single and in multiple skill environment in (Koedinger et al., 2011). In a single skill environment the most not mastered skill is selected, whereas in the multiple skill this behavior would present a too difficult content sequence. Consequently, the contents with a small number of not mastered skills are selected. Moreover, (Koedinger et al., 2011) point out how in ITS multiple skill exercises are modeled as single skill ones in order to overcome BKT limitations. We would like to stress that the sequencing requires an internal skills representation and consequently, together with the performance prediction algorithm, is domain dependent.
Another domain dependent algorithm used for performance prediction is the Performance Factors Analysis (PFM). In the latter the probability of learning is computed using the previous number of failures and successes, i.e. the representation of score is binary like in BKT (Pavlik et al., 2009). Moreover, similarly to BKT, a table connecting contents and skills is required.
Matrix Factorization (MF) is the algorithm used in this paper for performance prediction. It has many applications like, for instance, dimensionality reduction, clustering and also classification (Cichocki et al., 2009). The most common use is for Recommender Systems (Koren et al., 2009) and recently this concept was extended to ITS (Thai-Nghe et al., 2011). We selected this algorithm for several reasons:

1. Domain independence. Ability to model each skill, i.e. no engineering/authoring effort in individuating the skills involved in the contents.

2. Having comparable results with BKT latest implementations (Thai-Nghe et al., 2012).

3. Possibility to build the system with a common data set, i.e. without an exploratory corpus.

4. Small computational time on a 3rd Gen Ci5/4GB laptop and Java implementation: 0.43 s for building the model with already 122000 lines, negligible time for performance prediction.

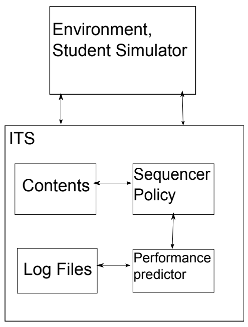


Figure 1: System structure in a block diagram.

3 CONTENT SEQUENCING IN ITS

The designed system consists of two main blocks. The first one is the environment and is represented by the students playing with the ITS. In our case this role is simulated because an on-line evaluation is required, i.e. the sequence optimality can be measured only after a student worked with it. We excluded the possibility of collecting an exploratory corpus because making practice with very easy and very difficult exercises in random order could be frustrating for the students, who could be children. Moreover, having a simulated environment could help gaining the confidence necessary for experimenting on humans. Anyway, after a first validation with real students, only a common data set collection will be necessary to set up the system with new contents, giving also the possibility to calibrate the environment and later use it for new sequencing methods.

The second block consists of different modules, i.e. the available contents, the previous interactions of the students with the system (log files), the student Performance Predictor and the Sequencer Policy. We chose a specific Performance Predictor and policy, but nothing is against using other ones in the future. When a student plays with the system the next exercise is proposed to him by the sequencer according to a policy. The Performance Predictor needs the log files of students playing with the contents considered to predict their scores in the next contents. The policy is applied in an adaptive way thanks to the information on the predicted scores shared between Performance Predictor and Sequencer. In the following Sections we will describe the different blocks represented in Fig. 1.

4 SIMULATED LEARNING PROCESS

We designed a simulated student based on the following assumptions. (1) A content is either of the correct difficulty for a student, or too easy, or too difficult. (2) A student cannot learn from too easy contents and learns from difficult ones proportionally to his knowledge level. (3) It is impossible to learn from a content more than the required skills to solve it. (4) The total knowledge at the beginning is different than zero. (5) The general knowledge of connected skills helps solving and learning from a content. The last assumption is more plausible because we assume to sequence activities of the same domain. For instance, in order to solve a fraction addition, a student needs more related skills: multiplication, fraction expansion etc. It is unlikely for a student to do a fraction expansion without knowing how multiplication works. At the same time the knowledge of multiplication will help him solving the steps on fraction expansion.

A student simulator is a tuple (S, C, y, τ) where, given a set $S \subseteq [0,1]^K$ of students, s_i is a specific student described as a vector φ^t. The latter is of dimension K, where K is the number of skills involved. $C \subseteq [0,1]^K$ is a set of contents, where c_j is the j–th content, defined with a vector ψ_j of K elements representing the skills required. $\varphi_{i,k} = 0$ means student i has no knowledge skill k, whereas $\varphi_{i,k} = 1$ means having full knowledge. $\tau : \mathbb{S} \times \mathbb{C} \to \mathbb{S}$ is a function defining the follow-up state $\varphi^{t+1} = \varphi^t + \tau$ of a student $s_i \in \mathbb{S}$ after working on contents c_j^t. In particular $\mathbb{S}$ and $\mathbb{C}$ are the spaces of the students and contents respectively. Finally, a function y defines the performance $y(\varphi_i, \psi_j)$. y and τ can be formalized as follows:

$$\begin{aligned} y(\varphi_i, \psi_j) &:= \max\left(1 - \frac{||\alpha||}{||\varphi_i||}, 0\right) \\ \tau(\varphi_i, \psi_j)_k &:= y(\varphi_{ik}, \psi_{jk})\alpha_k \\ \tilde{y} &:= y\varepsilon \end{aligned} \tag{1}$$

where

$$\alpha_k^{i,j} = \max(\psi_{jk} - \varphi_{ik}, 0) \tag{2}$$

and ε is proportional to the beta distribution $\mathcal{B}(p, q)$. We selected p and q in order to have $\tilde{y} \sim \mathcal{B}\left(y, \sigma^2\right)$, where σ^2 is the variance, i.e. the amount of noise. We chose the beta distribution because it is defined between zero and one as the score. Consequently it will not change the codomain of the y function. The characteristic of the formulas are the following. (1) The performance of a student on a content decreases proportionally to his skill deficiencies w.r.t. the required skills. (2) The student will improve all the required skills of a content proportionally to his performance

c_j	d_c	y	τ_k
$\{0.1, 0.1\}$	0.2	1	$\{0, 0\}$
$\{0.5, 0.6\}$	1.1	0.617	$\{0.12, 0.0617\}$
$\{0.5, 0.7\}$	1.2	0.515	$\{0.1, 0.1\}$
$\{0.9, 0.9\}$	1.8	0	$\{0, 0\}$

Table 1: Simulated learning process with two skills. A simulated student with $\varphi = \{0.3, 0.5\}$ scores y and learning τ after interacting with different contents c_j.

and his skill-specific deficiency up to the skill level a content requires. (3) As a consequence it is not possible to learn from a content more than the difference from the required and possessed skills. (4) A further property of this model is that contents requiring twice the skills level that a student has, i.e. $\|\psi_j\| \geq 2\|\varphi_i\|$, are beyond the reach of a student. For this reason his performance will be zero ($y = 0$). With a simple experiment without noise, we can show the plausibility of the designed simulator. We inserted values in Eqs. 1 as follows. Let us consider a system with two skills and represent the student knowledge as $\varphi = \{0.3, 0.5\}$. As it is possible to see in Tab. 1 with the increase of the content difficulty the learning increases and the score decreases until $\|\psi_i\| \geq 2\|\varphi_j\|$. The maximal difficulty level is equal to the number of skills since a single skill value cannot be greater than one.

5 VYGOTSKI POLICY AND MATRIX FACTORIZATION

5.1 Sequencer

The designed sequencer is defined as follows. Let $C \subseteq \mathbb{C}$ and $S \subseteq \mathbb{S}$ be respectively a set of contents and students defined in Section 4, d_{c_j} be the difficulty of a content defined as $d_{c_j} = \sum_{k=0}^{K} \psi_{j,k}$, $\tilde{y} : \mathbb{S} \times \mathbb{C} \rightarrow [0,1]$ be the performance or the score of a student working on the content, and T be the number of time steps assuming that the student is seeing one content every time step. The content sequencing problem consists in finding a policy:

$$\pi^* : (\mathbb{C} \times [0,1]) \rightarrow \mathbb{C}. \qquad (3)$$

that maximize the learning of a student within a given time T without any environment knowledge, i.e. without knowing the difficulties of the contents and the required skills to solve them. A common problem in designing a policy for ITS is retrieving the knowledge of the student from the given information, e.g. score, time needed, previous exercises, etc. The previous mentioned data types are just an indirect representation of the knowledge, which cannot be automatically measured, but needs to be modeled inside the system. Hence, integrating the curriculum and skills structure is the cause of the high costs in designing the sequencer. In this paper we try to keep the contents in the Vygotskis Zone of Proximal Development (ZPD) (Vygotski, 1978), i.e. the area where the contents neither bore or overwhelm the learner. We mathematically formalized the concept with the following policy, that we called Vygotski Policy (VP):

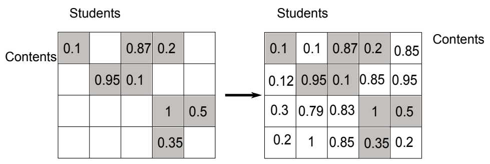
$$c^{t*} = \operatorname{argmin}_c \left| y_{th} - \hat{y}^t(c) \right| \qquad (4)$$

where y_{th} is the threshold score, i.e. the score that keeps the contents in the ZPD. The policy will select at each time step the content with the predicted score $\hat{y}^t$ at time t most similar to y_{th}. We will discuss further in the experiment session how to tune this hyper parameter and its meaning.
The peculiarity of the VP is the absence of the difficulty concept. Defining the difficulty for a content in a simulated environment as ours is easy, because we mathematically define the skills required. In the real case it is not trivial and quite subjective. Also the required skills are considered as given in the other state of the art methods like PFM and BKT, where a table represents the connection between contents and skills required. Without skills information not only BKT and PFM performance prediction cannot be used in our formalization, also sequencing methods (Koedinger et al., 2011) have no information to work with.

5.2 Matrix Factorization as Performance Predictor

Matrix Factorization (MF) is a state-of-the-art method for recommender systems. It predicts which is the future user ratings on a specific items based on his previous ratings and the previous ratings of other users. The concept has been extended to student performance prediction, where a student next performance, or score is predicted. The matrix $Y \in \mathbb{R}^{n_s \times n_c}$ can be seen as a table of n_c total contents and n_s students used to train the system, where for some contents and students performance measures are given. MF decomposes the matrix Y in two other ones $\Psi \in \mathbb{R}^{n_c \times P}$ and $\Phi \in \mathbb{R}^{n_s \times P}$, so that $Y \approx \hat{Y} = \Psi\Phi$. Ψ and Φ are matrices of latent features. Their elements are learned with gradient descend from the given performances. This allows computing the missing elements of Y and consequently predicting the student performances (Fig. 2). The optimization function is represented by:

$$\min_{\psi_j, \varphi_i} \sum_{j \in \mathbb{C}} (y_{ij} - \hat{y}_{ij})^2 + \lambda(\|\Psi\|^2 + \|\Phi\|^2) \qquad (5)$$


Students
Contents
Students
Contents

0.1		0.87	0.2	
	0.95	0.1		
			1	0.5
			0.35	

0.1	0.1	0.87	0.2	0.85
0.12	0.95	0.1	0.85	0.95
0.3	0.79	0.83	1	0.5
0.2	1	0.85	0.35	0.2

Figure 2: Table of scores given for each student on contents (left), completed table by the MF algorithm with predicted scores (right).

where one wants to minimize the regularized squared error on the set of known scores. The prediction function is represented by:

$$\hat{y}_{ij} = \mu + \mu_{cj} + \mu_{si} + \sum_{p=0}^{P} \varphi_{ip}^{T} \psi_{jp} \qquad (6)$$

where μ, μ_c and μ_s are respectively the average performance of all contents of all students, the learned average performance of a content, and learned average performance of a student. The two last mentioned parameters are also learned with the gradient descend algorithm.
The MF problem does not deal with time, i.e. all the training performances are considered equally. In order to keep the model up to date, it is necessary to retrain the model at each time step. MF has a personalized prediction, i.e. a small number of exercises needs to be shown to each student in order to avoid the so called cold–start problem. Although some solutions to these problems have been proposed in (Thai-Nghe et al., 2011; Krohn-Grimberghe et al., 2011), we will show in the experiment session that these aspects do not affect the performance of the system, neither they reduce its applicability. From now on we will call the sequencer utilizing the VP policy and the MF performance predictor VPS, i.e. Vygotsky Policy based Sequencer.

6 EXPERIMENT SESSION

In this section we show how the single elements work in detail. We start with the student simulator, continue with the VP and end with some experiments with performance prediction in different scenarios and noise. A scenario is represented by a number of contents n_c, a number of difficulty levels n_d, a number of skills n_k, and a number of students for each group n_t[1]. All the first experiments will have no noise, i.e. $\tilde{y} = y$.

[1]The MF was previously trained with n_s students that were used to learn the characteristic of the contents. Consequently, the dimensions of the MF during the simulated learning process are: $\Psi \in \mathbb{R}^{n_c \times P}$ and $\Phi \in \mathbb{R}^{(n_s+n_t)\times P}$, so that $Y \approx \hat{Y} = \Psi\Phi$.

6.1 Experiments on the Simulated Learning Process

To prove the operating principle of the simulator we tested basic sequencing methods in a particular scenario. The one we chose is described in Fig. 3, with $n_d = 7$ and $n_c = 100$. For representation purposes we created the contents with increasing difficulty, so that IDs implicitly indicates the difficulty[2]. The scenario mimics an interesting situation for sequencing, i.e. when more apparently equivalent exercises are available. The two policies we used are (1) Random (RND), where contents are selected randomly, and (2) the in range policy (RANGE), where each second content is selected in difficulty order. This strategy is informed on the domain because it knows the difficulty of the contents. We initialized the students and contents skills with an uniform random distribution between 0 and 1. Again for representation purposes we show the average total knowledge of the students that is represented by average of the students skills sum at each time step. We chose to perform the tests on 10 skills, i.e. the maximal total knowledge possible is equal to 10. We considered the scenario mastered when the total knowledge of the student group is greater than or equal to the 95% of the maximal total knowledge.
Fig. 4 shows the total knowledge of two groups of $n_t = 200$ students, one group was trained with random policy the other one with the in range policy. RANGE is characterized by a low variance in the learning process. RND, instead, has a high variance because the knowledge level of the students at each time step is given by chance. It is shown that the order in which the student practices on the contents is important for the total final learning. Fig. 4 also shows how the practice on too many contents of the same difficulty level, after a while, saturates the knowledge acquisition. All these aspects demonstrate that the learning progress is plausibly simulated.

6.2 Sensitivity Analysis on the Vygotski Policy

In order to evaluate the VP we created two more sequencing methods that exploit information not available in reality. The best sequencing knows exactly which is the content maximizing the learning for a student, for this reason we called it Ground Truth (GT). Vygotski Policy Sequencer Ground Truth (VPSGT), instead, uses the Vygotski Policy and the

[2]A content with ID 2 is easier than a content with ID 100, see Fig. 3

true score y of a student to select the following content. GT and VPSGT can be considered the upper bound of the sequencer potential in a scenario. In order to select the correct value of y_{th} we plot the average knowledge level at time $t = 11$ for the policy with different y_{th}. From Fig. 5 one can see that the policy is working for $y_{th} \in [0.4, 0.7]$, this because of the relationship between Eqs. 1 of the student simulator. In a real environment the interpretation of these results is twofold. First we assume y_{th} will be approximately the score keeping the students in the ZDP. Second, from a RL perspective, this value would allow finding the trade–off between exploring new concepts and exploiting the already possessed knowledge. Moreover, as one can see in Fig. 6, the policy obtains good results if compared with GT for some y_{th}, but for others the policy is outside the ZPD and the students do not reach the total knowledge of the scenario. In some experiments we noticed that the width of the curve in Fig. 5 decreased so that the outer limits of the y_{th} interval create a sequence outside the ZPD. As consequence we selected the value $y_{th} = 0.5$ that was successful in most of the scenarios.

6.3 Vygotski Policy based Sequencer

The scenario we selected for the tests with the VPS has $n_c = 200$, $n_d = 6$, $n_k = 10$ and $n_t = 400$. In order to train the MF–model a training and test data set need to be created. We used $n_s = 300$ students who learned with all the contents in order of difficulty. We used 66% of the data to train the MF–model and the remaining 34% to evaluate the Root Mean Squared Error (RMSE) for selecting the regularization factor λ and the learning rate of the gradient descent algorithm. We performed a full Grid Search and selected the parameters shown in Tab. 2. The sequencing experiments are done on a separate group of n_t students. In order to avoid the cold start problem 5 contents are shown to them and their scores added to the training set of the MF. For $T = 40$ the best content c_j^{*t} is selected with the policy VP for the n_t students, using the predicted performance $\hat{y}_{ij}^t$. In order to avoid the deterioration of the model, after each time step the model is trained again once all students saw an exercise. A detailed description of the algorithm of the sequencer can be found in Alg. 1, where Y_0 is the initial data set. As one can see in Fig. 7 the VPS selects the first content similarly to RANGE. Then the prediction allows to skip unnecessary contents speeding up the learning. Once the total knowledge arrives around 95%, the selection policy cannot find contents that fit to the requirements. Consequently the students learn as slow as the RND group, as one can see from the saturating curve. In Fig. 8 GT selects the contents in difficulty order skipping the unnecesary ones. The average sequence of the VPS, instead, is also with approximately increasing difficulty but in an irregular way. This is due to the error in the prediction performance. In conclusion the proposed sequencer gains 63% over RANGE and 150% over RND. The presented experiments show how the MF is able, without domain information, to model the different skills of students and contents and partially mimics the best sequence, which is the one selected by GT in Fig. 8.

Parameters	Choice
Learning Rate	0.01
Latent Features	60
Regularization	0.02
Number of Iteration	10

Table 2: Parameters MF

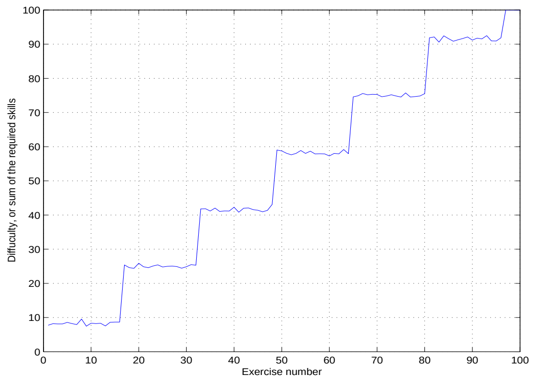


Figure 3: Scenario: Content Number and difficulty level.

Algorithm 1: Vygotski Policy based Sequencer

```
   Input: $\mathbb{C}$, $Y_0$ $\pi$, $s_i$, T
1  Train the MF using $Y_0$;
2  for $t$ = 1 to T do
3      for All $c \in \mathbb{C}$ do
4          Predict $\hat{y}(c_j, s_i)$ Eq. 6;
5      end
6      Find $c^{t*}$ according to Eq. 5;
7      Show $c^{t*}$ to $s_i$ with Eq. 1;
8      Add $y(s_i, c^{t*})$ to $Y_t$;
9      Retrain the MF; // Corrects over- or
       underestimation by the MF
10 end
```

6.4 Advanced Experiments

In this section we want to show the correct working of the sequencer changing the parameters of the scenario

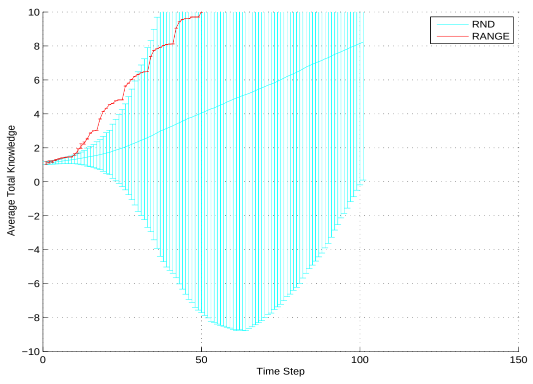


Figure 4: Comparison between RANGE and RND. Average skills sum, i.e. knowledge, over all the students with variance

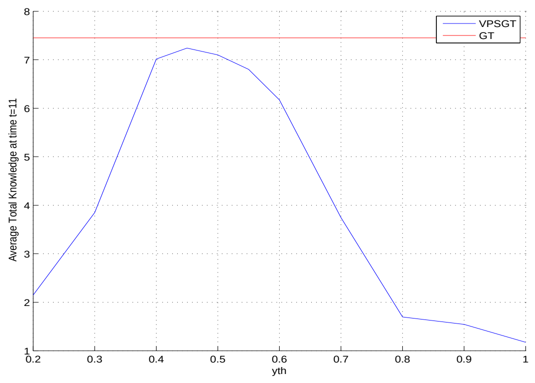


Figure 5: Policy selection, i.e. the performance of the Vygotski policy with different y_{th} at the same time step. Different groups of students learned with the Vygotski policy with y_{th} values going from 0.1 to 0.9. As shown in the figure the knowledge levels change according to the y_{th} selected.

n_k and n_c and later adding noise. In order to do so we consider the percentage of gain of VPS with respect to RANGE considering a specific time step $t = 30$ with $n_k = 10$ and $n_d = 6$. As one can see in Fig. 10 the gain obtained by the sequencer depends on the available number of contents. Since in RANGE each second

Policy	Description
Random (RND)	Contents are selected randomly
In Range (RANGE)	Each second content is selected in difficulty order.
Ground Truth (GT)	Selects the contents according to which is the one maximizing the learning.
Vygotski Policy based Sequencer Ground Truth (VPSGT)	Chooses the next content using the policy and the real score of a student.
Vygotski Policy based Sequencer (VPS)	Chooses the next content using the policy and the predicted score of a student.

Table 3: Baselines Description

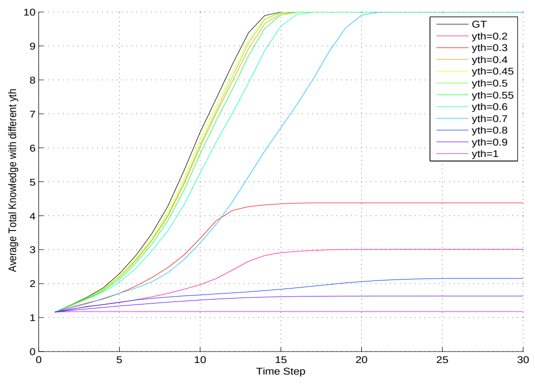


Figure 6: Effects of the different y_{th} on the final knowledge of the students. The learning curves of the student groups that learned with the different Vygotski policies.

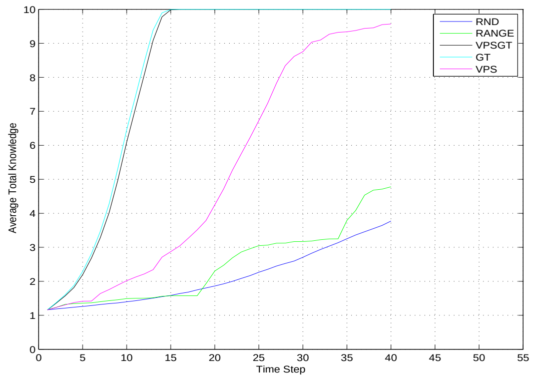


Figure 7: Average Total Knowledge. How the average learning curve of the students changes over time.

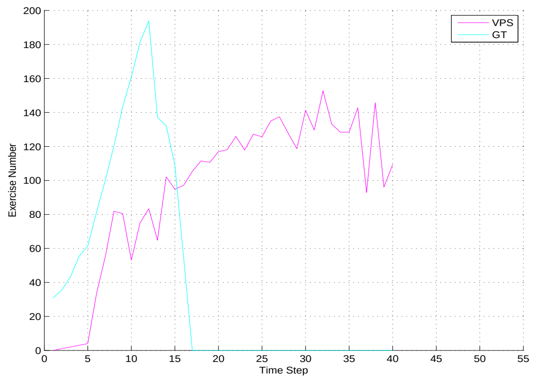


Figure 8: Average sequence selected by the GT and the VPS. The VPS approximate the optimal sequence that GT computes thanks to the real skills of the students.

content is selected, with $n_c < 60$ there are not enough contents for all time steps. Our sequencer can adapt without problems to the situation. The optimal point for the in range policy is when $n_c = 60$ because there is exactly the necessary number of contents for the student to learn. When $n_c > 60$ the students see many

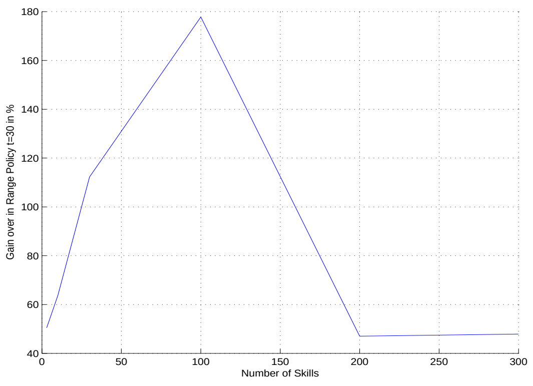


Figure 9: Gain over RANGE policy varying n_k. The gain is measured at a specific time step in percentage, considering the average knowledge level of the two groups of students, one practicing with the RANGE sequencer and one with the VPS.

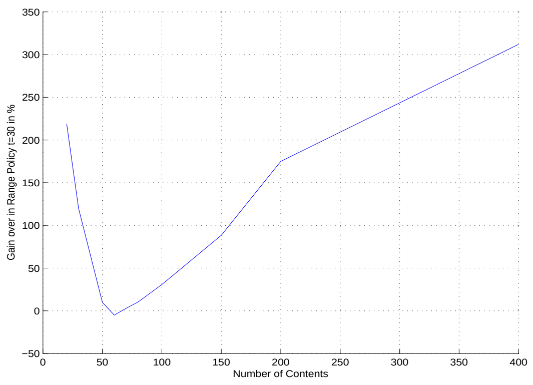


Figure 10: Gain over RANGE policy varying n_c. The gain is measured at a specific time step in percentage, considering the average knowledge level of the two groups of students, one practicing with the RANGE sequencer and one with the VPS.

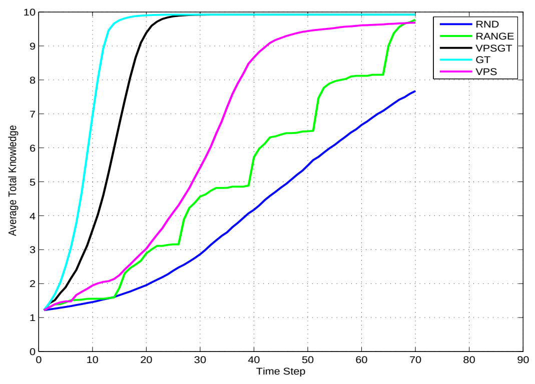


Figure 11: Effect of noise in the simulated learning process. Beta distribution noise with $\sigma^2 = 0.1$.

unnecessary contents and consequently learn slower. Fig. 9 with $n_c = 60$, $t = 30$ and $n_d = 6$ shows the dependencies between skills and gain. The experiments demonstrated a high adaptability of the sequencer to the different scenarios.
Last we experimented the results robustness adding noise, i.e. $\tilde{y} = y\varepsilon$. We experimented with $\sigma^2 \in [0, 0.5]$. As one can see in Fig. 11 with $\sigma^2 = 0.1$ the Vygotski sequencers are still able to produce a correct learning sequence but more time is required. The VPSGT is the one that suffered the most from the introduction of noise, probably related to the selection of y_{th}.

7 CONCLUSIONS

In this paper we presented VPS, a sequencer based on performance prediction and Vygotski concept of ZPD for multiple skills contents with continuous knowledge and performance representation. We showed that MF is able dealing with the most actual problems of Intelligent Tutoring Systems, like time and personalization, retrieving automatically skills required and difficulty. We proposed VP, a performance based policy that does not require direct input of domain information, and a student simulator that partially overcomes the problem of massive testing with real students. The designed system achieved time gain over random and in range policy in almost each scenario and is robust to noise. This demonstrates how the sequencer could solve many engineering/authoring efforts. Nevertheless, an experiment with real students is required to better confirm the validity of the assumptions of the simulated learning process. A different evaluation is required for the performance prediction based sequencer. Since MF was already tested on real data, the main risk, in this case, is represented by the VP, which requires the tuning of the threshold score y_{th} on real students. Another minor risk, the over- or underestimation of the student's parameters by the performance predictor, was already addressed in (Koedinger et al., 2011) and is minimized here by retraining the model. In conclusion, to use VPS, no further analysis are required, since the MF will reconstruct the domain information, thanks to continuous score representation. The exploitation of performance predictors able to deal with continuous scores and knowledge representation are the future of adaptive ITS. With the results obtained in this paper we plan to extend such an approach also to other intervention strategies to further reduce the engineering efforts in ITS.

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