SimStu-Transformer: A Transformer-based Approach to Simulating Student Behaviour

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Abstract. Lacking behavioural data between students and an Intelligent Tutoring System (ITS) has been an obstacle for improving its personalisation capability. One feasible solution is to train "sim students", who simulate real students' behaviour in the ITS. We can then use their generated behavioural data to train the ITS to offer *real students* personalised learning strategies and trajectories. In this paper, we thus propose SimStu-Transformer, developed based on the Decision Transformer algorithm, to generate learning behavioural data.

Keywords: Student Modelling · Decision Transformer · Intelligent Tutoring Systems · Behavioural Patterns.

1 Introduction

The past decade has seen the rapid development of Machine Learning (ML) in many fields, including Intelligent Tutoring Systems (ITS). Unlike traditional ITS, which are time-consuming to build, recently proposed data-intensive ITS are more efficient, but require a large amount of data to support the ML models, [11]. Unfortunately, the lack of student behavioural data has become one of the most significant barriers for ITS breakthroughs, akin to the scarcity of labelled data in several other AI domains [12]. Previous studies have proposed various approaches to address this problem. For example, building Reinforcement Learning agents to simulate student behavior to train the ITS [5], simulating students' mastery of knowledge through Knowledge Tracing (KT) [7], or classifying students into different clusters based on their social interaction pattern to predict their behaviour [8]. However, none of these approaches has effectively solved this problem. Thus, in this paper, to tackle this challenge, we aim at answering:

How to create adequate high-fidelity and diverse simulated student behavioural data for training ITS?

The Transformer-based strategy allows ITS to capture a small amount of real student behavioural data and provides it to a generator that generates a large amount of simulated student behavioural data, which can subsequently be used to train the ITS alongside the real data. In this paper, we propose "SimStu-Transformer" based on the Decision Transformer [2].

We adopt the 'sim student' approach [1], to simulate student behaviour. We apply group-level student modelling [4], to identify the "optimal" behavioural patterns that may result in better learning outcome. The results suggest that our model can well imitate student learning behaviour, and that it outperforms the traditional imitation learning method [6]. Our key contributions are twofold:

1. We designed a student learning behaviour simulation method to provide adequate data for ITS.
2. Our results showed a trained SimStu-Transformer model can simulate real student behaviour and surpass traditional imitation learning methods.

2 Experiment

Architecture. Our SimStu-Transformer is developed based on the Decision Transformer [2], initially proposed by Chen*et al.* It consists of an encoder and a decoder that simulate the joint distribution of student 'returns-to-go', 'states', and 'actions'. It divides student interactive trajectory sequences into two halves, one for the encoder's input and the other for the decoder's output [10]. The encoder then receives the first half of the trajectory sequence embeddings as input, and outputs a trajectory to the decoder. To construct the final output trajectory, the decoder takes a shifted embedding trajectory as input.

Data. Our data is from EdNet [3] - the largest student-ITS interaction benchmark dataset in the field of AIED/ITS. We conducted our experiments using the EdNet-KT4 sub-dataset, which provides more detailed interaction data than the other three sub-datasets. EdNet-KT4 contains 297,915 students' data with access to specific features and tasks. 1,000 students (a total of 861,247 action logs) were randomly selected for our experiments (200 students as the training data; 200 as the test data; 600 to compare with the simulated data). Students were divided into 5 groups based on their scores, due to the consideration of the possible correlation between learning performance and learning behaviour (Group 1 to Group 5: "very good" to "very poor"). The training data and the test data were partitioned by stratified sampling with such grouping strategy.

Trajectory Representation The gap between the individual timestamps is used to replace the actual timestamps. The large UNIX time integers are reduced to small values. We also exclude highly sparse data from the modelling data. *'action_type'* is used to imitate students behaviour, which is denoted by a in the Decision Transformer Trajectory τ. *'user_answer'*, denoted by r, is used for evaluating student performance, thus partitioning them into groups.The correctness of student's answers were examined. *'item_id'* is used for evaluating the feasibility of the learning paths, which takes as the state of the student and is denoted by s. Due to the fact that *'user_id'* does not affect or represent student behaviour, we choose to generate it randomly, after the SimStu-Transformer generation procedure ends.

Experimental Design The SimStu-Transformer was implemented using the Pytorch framework and trained on an Nvidia RTX 3090 GPU. We used the Adam optimiser with batch size of 64. We set Adam betas as (0.9, 0.95). The initial learning rate was 0.0006 and the dropout rate was 0.1. Two experiments were conducted to access the SimStu-Transformer.

In the first experiment, the similarity of the data generated by the SimStu-Transformer model was compared with the real data using Pearson Product-Moment Correlation Coefficient (PPMCC). The same training and test data was provided to the Behaviour Cloning model proposed by Torabi [9] in the second experiment, which yielded 600 student trajectory data (a total of 4,413,561 actions) and its results were compared with the real student data. We used RELU as the nonlinearity function, with standard batch size of 64. We set the initial learning rate as 0.0001 and the dropout rate as 0.1. We forcused on examing the distribution of 'elapsed time' (i.e., the amount of time a student works on a specific exercise) between the Behaviour Cloning method and the SimStu-Transformer with real student data by PPMCC.

Result and Discussions Our results discovered some statistical similarities between the distributions of real student data and simulated student data , such as group sizes and the difference in the amount and frequency of actions in each group. Differences were only observed in the actions that occur less frequently, such as *'pay'* and *'undo_ erase_ choice'*. The resulting PPMCC value of all actions is equal to 0.714, which implies that the simulated student data is 71.4% similar to the actual student data in the average distribution of actions.

Figure 1 shows the distributions of elapsed time of real student (on the left), SimStu-Transformer simulated student (in the middle), and the Behaviour Cloning model simulated student (on the right). It can be seen that our SimStu-Transformer model outperforms the Behaviour Cloning model, as the data simulated by SimStu-Transformer is more similar to the real data (The PPMCC value: 0.762 vs. 0.683).

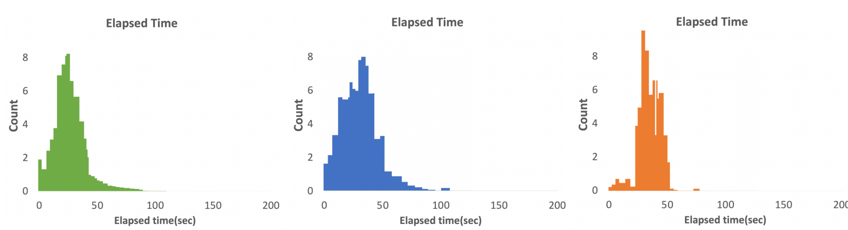

Fig. 1. Elapsed time of Real Student Data (left), SimStu-Transformer method (middle), and Behaviour Cloning method (right).

3 Conclusions and Future Work

This paper presents a Transformer-based technique (SimStu-Transformer) to generate data for ITS training by modelling student behaviour. We use EdNet to train our model, which generates learning behaviour data that can be used to simulate individual students' learning trajectories. This method may benefit ITS training by compensating for the scarcity of real student data.

In the future, we aim to establish measurements to assess the fidelity and variety (coverage) of the simulated students in order to produce data that is as diverse as real student data. We also plan to address the impact of infrequent individual activities, such as *pay*, by evaluating different weights for different actions, for example. Finally, we plan to feed the simulated data into a real ITS to investigate if it can optimise the ITS training process, with a special focus on its effects on personalisation and adaption capabilities.

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