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RESEARCH ARTICLE

Learning Behavior Analytics for Adaptive Path Optimization in Online Education Systems

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Abstract

The growing multiplicity of learner behaviour in online education systems has opened up the constraints of fixed learning paths that do not move with the individual engagement, performance and the advanced knowledge. Although the available data driven methods provide various degrees of personalization, most of them are based on either heuristic decision rules or black-box machine learning models that are not optimised and interpretable. The current paper introduces a behaviour-sensitive behaviour adaptive learning path optimization framework, which combines learning behaviour analytics and a sequential optimization formulation. The dynamics between learners are modelled as a multidimensional state representation of dynamics of engagement, mastery and performance. According to this model, adaptive learning path selection is transformed into a sequence of decision-making processes, and a behaviour-conscious optimization algorithm is created, which can be used to dynamically determine a learning activity that leads to the greatest cumulative learning increase. The so-called framework is assessed based on an online learning dataset and compared against a set of the methods that are based on the static and machine learning. The experiments prove increased learning outcome and enhanced course completion of the course, which proves the appropriateness of behaviour-based adaptive optimization. These results demonstrate that behaviour modelling in terms of formalisation and adaptive optimization can be employed to a large extent to personalise and increase the effectiveness of learning in online education settings.

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Introduction

The online education systems have developed at a pace because of their capabilities of scaling and offering flexible access to learning materials.[1, 6] Nevertheless, even after this advancements, a majority of platforms still use fixed or fixed learning paths which presuppose the homogeneity of learner behaviour and the linear learning development .[9, 12] As a matter of fact, learners demonstrate significant heterogeneity in terms of engagement, prior knowledge, learning speed, and performance which mostly results in inefficient learning experience, decreased engagement, and low course completion rates with enforced fixed curricula.[5], [6]. To manage the diversity of the learners, adaptive learning systems have been pioneered to make the content being offered dependent on the interactions of the learner.[1-3] Current methods are largely based on the use of rules based sequencing or machine learning based recommendation model.[8, 11] Rule-based systems provide transparency at the cost of flexibility to changing conditions of learners,[9] whereas data-driven models have the ability to model the intricate interaction patterns but are, in many cases, a black box, with no distinct goals of optimization.[7, 8] Consequently, heuristic decisions, or short term decisions are made by many adaptive systems, and they fail to explicitly consider the result of cumulative learning.[2, 4] The analytics of learning behaviour offers a systematic way to capture the interactions of learners such as the dynamics of engagement, performance trends, and the progression of learning.[10, 11] Such behavioural cues can be used to make adaptive learning choices when properly modelled.[2, 3] But successful application of behaviour analytics in order to be translated into optimal learning path resolution is still difficult because of the dynamic and sequentially of learning processes.[4, 7] Most of the current frameworks are considered either on retrospective analysis or immediate accuracy of recommendation but not on long-term learning efficiency.[10, 11] Adaptive learning path selection can also be considered a sequential decision-making question where learning processes are decided based on the existing learner state in order to optimise the accumulated learning rewards.[4, 7] This sort of formulation makes it possible to handle trade-offs between engagement, mastery development and instructional complexity in a principled manner.[3, 6] Although this opinion is relevant, this view of online education has not been used to its maximum in practise, where optimization is implicit or absent in many web-based systems of education.[2, 8] The given paper will introduce a behaviour-conscious framework of adaptive learning path optimization, which combines the learning behaviour analytics with a formal sequential optimization model.[2, 4, 7] A multidimensional state representation that encapsulates the dynamics of engagement, mastery and performance is used to represent the learner interactions.[9, 10] In view of this representation, an adaptive optimization algorithm is the dynamically chosen learning activities with regard to changing learner states.[3, 7] The efficacy of the suggested framework is tested by the experimental analysis of an online learning dataset where the prescriptions prove to be more effective in the study and approaches that rely on machine learning and statistical methods are analysed in comparison to the levels of learning and course completion.[2, 5]

Related Work

In the adaptive learning system research, the shift of constant curriculum design has been replaced by data-driven methods of personalization in order to tackle learner heterogeneity within an online learning context.[9, 12] The earlier learning management systems mainly used either the rule-based or statical learning paths whereby instruction content was presented based on the pre-defined sequences as used.[9, 11] Even though these strategies are clear and simple to execute, they presuppose homogeneous learner performance and a linear advancement of the knowledge, which restricts their capacity to change in response to the fluctuations in the engagement of learners, their performance, and the level of mastery acquisition.[5, 6] The growing accessibility of learner interaction data has led to the overall use of learning analytics and machine learning algorithms to personalise learning content.[1, 2] These methods make use of behavioural information like those in the clickstream activity, quiz performances, and time-on-task to suggest learning materials or forecast learner achievements.[2, 8] Although the complex interaction patterns can be represented by a data-driven model, many of them are implemented as black-box architecture and are concerned with the short-term accuracy of the recommended results.[7, 8] In addition, they tend not to have clearly stipulated optimization goals and, this way, it becomes hard to state that adaptive decisions result in better long-term learning results.[4, 10]

A current research has investigated adaptive learning structures with respect to serial decision making frameworks, such as the reinforcement learning and adaptive control schemes.[4, 7] These methods also seek to dynamically guide learning directions based on interactions between learners. However, despite their potential, current algorithms often make use of simplified representations of learners or often reward formulations which fail to reflect the multidimensional nature of learners behaviour.[3, 10].There is also a great issue of scalability, understand ability, and also practicability of deployment in the real-life online education platform.[5, 6] All in all, the current adaptive learning methodologies have an inclination of focusing on learner modelling, adaptation, and optimization separately. The methods that are not based on machine learning can be described as static and rule-based, lack responsiveness,[9] machine-learned based systems are predictive instead of optimal,[8] and sequential-based models of decision-making frequently utilise limited behavioural representations.[4, 7] Such restrictions indicate that a unified system that integrates organised learning behaviour analytics and clear adaptive optimization is required.[1, 2] The current contribution seals this gap wherein the framework of multidimensional learner behaviour modelling is unified over a sequential optimization based learning path selection framework.[3, 7]

Problem Formulation and System Model.

This part gives the system model and formally describes learning behaviour representation that is used to optimise adaptive learning paths. The objective is to simulate the interactions amongst learners in an organised way to facilitate sequential decisions.

Learning Behavior Representation

The behaviour of learners in an online learning setting develops dynamically as time goes by as the learners are exposed to teaching material and tests. The state of the behaviour of learner iii at learning step is described by a multidimensional state of a learner. In (1) the learner state vector is given as.

$$s_i(t) = \begin{bmatrix} e_i(t) \\ c_i(t) \\ p_i(t) \end{bmatrix}, \tag{1}$$

where denotes the engagement level of learner at time, represents the concept mastery score reflecting the learner's knowledge state, and corresponds to a performance metric such as quiz accuracy or response latency. All these elements define the level of interaction, the cumulative knowledge and learning performance in the present case of the learner. The state impaction of (1) is made to be compact, easy to interpret, and yet has enough behavioural information to make adaptive learning decisions. Modelling the behaviour of the learners as a time-varying state vector, the process of learning can be dealt with as a dynamic system where the instructional actions affect the future states of the learner. This is the basis of the optimization framework of adaptive learning paths which will be presented later in the subsection below.

Formulation of Adaptive Learning Path Optimization.

Adaptive learning path selection is a formulated problem on sequential optimization, based on the learner behaviour representation given in (1). At each learning step, the system selects a learning activity according to the current learner state with the objective of maximizing cumulative learning outcomes over a finite horizon. The optimization goal of adaptive learning path is presented in (2) as

$$\max_{\pi} \mathbb{E}\left[\sum_{t=1}^{T} \gamma^t R\big(s_i(t), a(t)\big)\right], \tag{2}$$

where denotes the learning path policy that maps learner states to learning activities, represents the learning activity selected at step , and is the reward function that quantifies learning gain while penalizing factors such as cognitive overload. The discount factor controls the relative importance of immediate and future learning rewards. The optimization in (2) is subject to the following constraints:

$$, \quad a(t) \in \mathcal{A}, \; s_i(t+1) = f\big(s_i(t), a(t)\big) \tag{2}$$

where denotes the set of available learning activities, and represents the learner state transition function that captures how instructional actions influence subsequent learner behavior. The state change is based on the transformation of engagement, learning and performance, where learners are exposed to the activities of choice. In (2), the adaptive choice of learning paths is explicitly modelled as the sequencing decision-making process to allow systematic optimization of the learning outcomes in the long term. This structure merges the learner behavior modeling with a clear optimization goal in order to promote principled adaptation in contrast to the heuristic or short-sighted learning suggestions.

Postulated Adaptive Learning Algorithm Behaviour-Aware.

This section gives the suggested behaviour-sensitive path optimization procedure of adaptive learning. The formulation used in Section 3 is operationalized by the algorithm, which plays off on the data of interaction through two steps: (i) estimates the learner state based on these interaction data, (ii) chooses the next learning experience or activity by applying a policy, and (iii) refines the policy by using observed feedback of the learner. The general algorithm can be summarised in Algorithm 1 and involves making serial decisions and acting with a finite learning horizon with the constraint that the activities chosen are feasible activities.

Algorithm 1: Adaptive Learning Path Optimization

Input: Learner interaction data, activity set, learning horizon, discount factor, initial policy , update rate
Output: Optimized learning path policy

1: Initialize policy π ⟵ π0

2: Initialize learner state s_i(0) using D (or a prior)

3: for t = 0 to T−1 do

4: Extract behavioral features x_i(t) from D

5: Update learner state s_i(t) using x_i(t) // state in (1)

6: Select activity a(t) ~ π(· | s_i(t)) such that a(t) ∈ $\mathcal{A}$

7: Deliver activity a(t) and observe feedback y_i(t)

8: Compute reward r(t) ⟵ R(s_i(t), a(t), y_i(t))

9: Update next state s_i(t+1) ⟵ f(s_i(t), a(t), y_i(t))

10: Update policy π using (s_i(t), a(t), r(t), s_i(t+1)) with rate η

11: end for

12: return π*

The recommended algorithm is interpretable in the sense that it explicitly scales the learner state based on the multidimensional representation in (1) and optimization of decisions based on cumulative objective based on (2). The policy update step is intentionally made generic so as to allow lightweight online adaptation; policy update may be based on bandit-style updates, gradient-based policies improvement, or other efficient and computationally efficient policy update rules based on deployment considerations.

Experimental Setup

Dataset Description

The online learning dataset which captures the interactions of the learners in a learning management offline is used to evaluate the proposed behaviour-aware adaptive learning framework. This requires a dataset that includes records of interactions, assessment records, and activity data (enclosed in time stamps) data collected on several courses. The behavioural features of each learner record are constructed by outfitting the clickstream activity, quiz performance and time-on-task data, which are then utilised to build the learner state description specified in (1). In order to obtain a detailed assessment of adaptive learning behaviour, the dataset has learners of different levels of engagement, learning rates, and performance distributions. The variety of interaction patterns allows to evaluate the suggested algorithm in cases of heterogeneous learning. To achieve reproducibility and controlled experimentation, interaction records (which are either missing or noisy) are filtered and standardised through normalisation and filtering techniques. Table 1 gives a summary of the key characteristics of the dataset that had been used in the experiments.

Table 1: Dataset Characteristics

Parameter	Value
Number of learners	1,200
Number of courses	6
Average sessions per learner	18
Total interaction records	21,600
Features per learning session	12
Assessment types	Quizzes, assignments
Data types	Clickstream, scores, time-stamps

Baseline Methods

In order to test the performance of the proposed behaviour-aware adaptive learning path optimization framework, the performance quality of the framework is compared to the representative baseline strategies widely adopted in the online education systems. The chosen baselines represent varying degrees of adaptivity, optimising potential, and interpretability, which gives an equilibrium comparison of conventional and data-driven methods. The Static Path is the first baseline where the learners use a set sequence of curriculum which does not change based on the learner behaviour or performance. Such strategy is a conventional LMS-based learning paths and can be considered a lower-bound benchmark. The second baseline is a ML-Based Recommendation approach, which uses data-driven models that are used to offer learning activities, depending on the previous interactions with the learner. This method may be partial in terms of adaptivity, and often it is a black-box style of model. The suggested approach is compared to these baselines to point out the advantages of utilising both structured modelling of learner behaviour and overt sequential optimization. Table 2 presents a qualitative comparison between the two approaches to the baseline methods and the suggested approach.

Table 2: Baseline Comparison Methods

Method	Adaptivity	Optimi-zation	Explain-ability
Static Path	No	No	High
ML-Based Recommen-dation	Partial	No	Low
Proposed Method	Yes	Yes	Medium

Results and Discussion

Learning Performance Improvement

The general performance of the adaptive learning path optimization framework that is proposed is measured by assessing the change in the average learning gains at every learning step. Figure 1 demonstrates the mean learning improvement with respect to learning cycles of the dynamic path, ML-based recommendation, and the recommended adaptive optimization strategies. Learning gain measure is the averaged progression of learning in all the learners on a normal range. As illustrated in Figure 1,

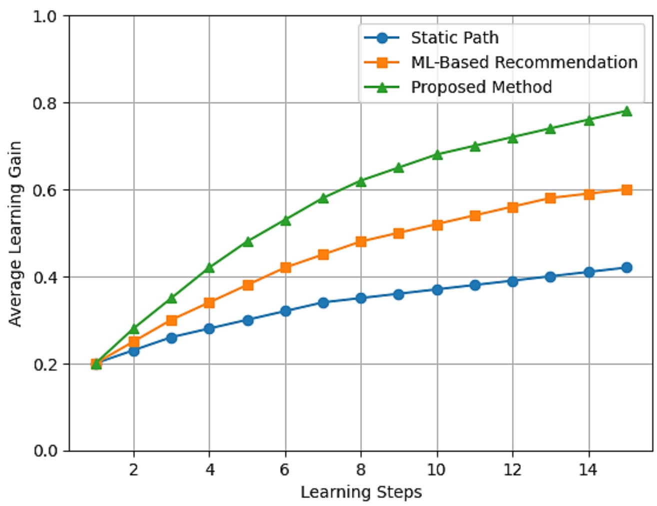

Fig. 1: Average Learning Gain vs. Learning Steps

the static path approach is slow and almost linear in growth thus lacking flexibility to the needs of the learners. The performance of the ML-based recommendation approach provides greater learning improvements than the stationary baseline that demonstrates the advantage of data-driven personalization. Nonetheless, its convergence rate is still rather average which indicates that the quality of recommendation in itself does not predetermine an efficient progress of learning in the long run.

On the contrary, the suggested approach shows much faster convergence and steady greater gains in the learning process. Alteration in learning gain is rapid in the initial steps in learning reflecting successful adjustment to the states of the learner whereas the greater latter gain corresponds to enhanced knowledge acquisition in the cumulative manner. This action validates that by explicitly modelling the learner behaviour and sequential optimization of learning tracks, more efficient learning tracks are realised. On the whole, the findings of Figure 1 demonstrate that the proposed behaviour-aware optimization framework can indeed expedite learning process and enhance learning efficiency in comparison with those of the baseline of the proposed solutions i.e. the use of the static schemes and ML-based schemes.

Engagement and Completion Rate Analysis

The course completion rate is a system-level performance measure that is used to assess the learner engagement and retention. Figure 2 shows the completion rate of the course under the conditions of the static path, recommendation based on the machine learning methods, and the suggested behaviour-awareness adaptive optimization strategies. This measure is a depiction of the percentage of learners who complete the course within each learning

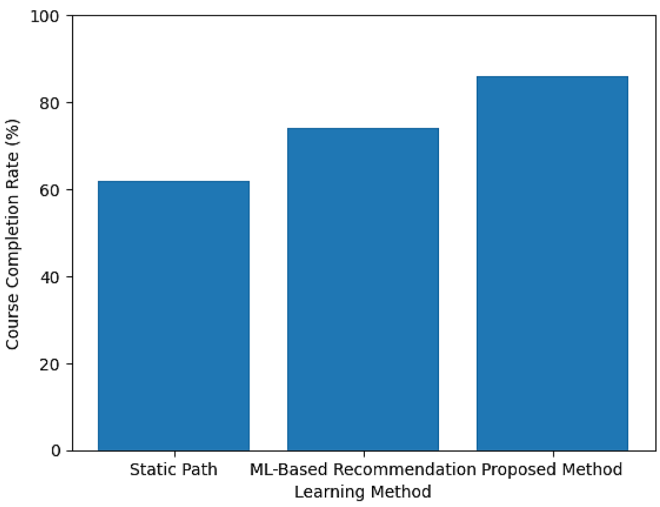

Fig. 2: Course Completion Rate Comparison across Methods

path strategy. As it is depicted in Figure 2, the approach of the static paths has the lowest completion rate, meaning that hardly any learners are retained in case the adaptive content sequencing is not involved. The rate of completion provided by the ML-based recommendation technique showed significant completion rate improvement which indicates that personalization based on data can partially contribute to the motivational level of learners. But it is limited since it does not explicitly optimise the learning trajectories.

This is also evidenced by the fact that the proposed approach attains the highest course completion rate among all the approaches that have been assessed, which makes behaviour-aware adaptive optimization effective in keeping the learners engaged in the course in the long-term context. The proposed structure ensures better retention by dropping out less and being more responsive to the changing learning states of the learners, lowering the levels of disengagement and dropout. These findings reveal that combined structured learner behaviour modelling with adaptive optimization not only improves performance in learning, but also has a positive effect on long-term engagement of learners. In general, the comparative outcomes in Figure 2 evidence that the proposed method has some obvious benefits in terms of retention and completion of the course as compared to both the fixed and ML-based approaches towards course selection.

Scalability and System Architecture.

To explain the behaviour-aware adaptive learning system framework behaviour, Figure 3 shows the structure of the system that has behaviour analytics, sequential optimization, policy selection, and feedback-based policy updates due to the logging of learner interaction. Unlike the result figures, Figure 3 is there to be interpreted and understandable and not to claim performance. As shown in Figure 3, data on learner interaction (e.g., clickstream events, quiz responses, and timestamps) enter into the behaviour analytics module and are first processed to obtain features and estimate learners state variables. The adaptive optimization engine is based on these state estimates and calculates an optimized learning policy; it re-calculates this policy according to the observed feedback. Learning activity Selector is then used to implement the optimised policy when the learning activities are selected which are personalised and the response of the learner is also the final step where the learner provides feedback which contributes to the continuous adjustments.

Scalability wise, the architecture is scalable, with the real LMS environments since the main computation could be given in lightweight modularized software. The process of

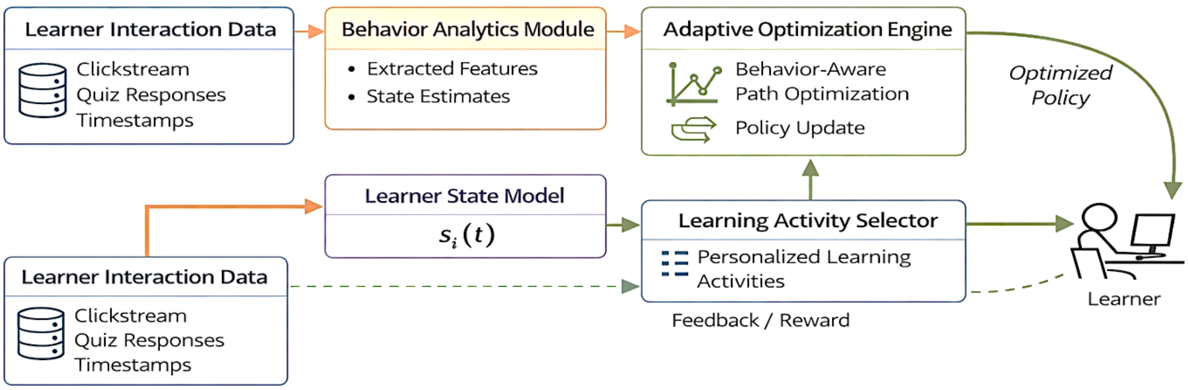

Fig. 3: Behavior-Aware Adaptive Learning System Architecture

feature extraction and state estimation can be performed in real time by applying incremental updates whenever an interaction event occurs, whereas policy update can be performed periodically (e.g. after every session) to minimise the computation costs. This segregation allows investment of flexible deployment plans such as centralized optimization of small to medium devices or distributed processing of large scale systems with thousands of simultaneous learners. Another important trade-off in the proposed system is the trade-off of quality of personalization against the cost of computation. The sets of behavioral features and more frequent updates of the policies may make adaptivity better, though they augment runtime overhead and infrastructure investment. This trade-off can be dealt with through practical deployments through the use of compact representations of states, batching of updates and limiting the candidate activity set during selection. In general, Figure 3 shows that the suggested framework justifies the clear feedback-based workflow without compromising the structure of scalable LMS implementation.

7. Conclusion and Future Work

The paper proposed an online education system behaviour-aware optimal framework, which is a pivotal adaptive learning path-optimization framework to the limitations of both rigorous curricula and the approach of heuristic recommendations. The proposed structure can adapt learning trajectories dynamically in response to dynamic states of the learner with the help of learning behaviour analytics and sequential optimization formulation. A small state representation is used to capture learner interaction, development of mastery and dynamics of their performance together, which gives an organised basis of adaptive decision-making. The experimental outcomes proved that the given method converts to learning faster and converts to more cumulative learning than the baselines basing on either the static learning or machine-based learning. Besides, better completion rates of the courses are a sign that behaviour-aware optimization can increase engagement and retention of the learners. These results confirm that dynamically modelling the behaviour of learners and ensuring learners have more and more efficient learning paths over time is more effective and efficient in the context of a customised learning experience. Although it is effective, there are numerous ways in which the current framework can be expanded. A more detailed representation of the learners will be examined in future through graph-based models or hierarchical state models to identify the dependence between the learning concepts. Formulations of policy learning involving reinforcement learning and multi-objective optimization can also be explored to balance policy learning, engagement and cognitive load more explicitly. Moreover, the issue of including multimodal cues of behaviour, including video exchanges, speech, or physiological reactions can also enhance the accuracy of adaptation. Lastly, extensive deployment tests will be done on actual learning management systems to test their long term scalability and resiliency based on varying population of learners.

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