Temporal Trajectory Modeling of Student Programming Behavior Using Dynamic Time Warping on Online Judge Data

Bikash Sasmal[1], Krupali Solanki[2], Shivani Bhamani[3]

[123]*Assistant Professor, Department of Information Technology, Gyanmanjari Innovative University, Gujarat, India*

Abstract - *Educational Data Mining (EDM) in programming education has grown significantly with the proliferation of Online Judge (OJ) platforms. Existing studies on student performance prediction and knowledge tracing predominantly rely on static or cumulative behavioral features, ignoring the temporal shape of a student's learning trajectory. A student whose error rate drops steadily from week one is fundamentally different from one whose error rate plateaued after an initial improvement yet both may yield identical aggregate metrics. This paper proposes DTW-TrajClust, a novel framework that applies Dynamic Time Warping (DTW) to model and cluster the temporal evolution of student programming behavior using the According OJ dataset containing 4,046,652 submissions from 27,444 university students over six years. Weekly error-rate time series are constructed per student, and DTW-based k-medoids clustering identifies five behaviorally distinct trajectory archetypes: Steady Improvers, Early Plateauers, Struggle-Recovery learners, Chronic Stagnators, and Volatile Learners. Experimental results demonstrate that trajectory-aware features outperform static baselines and state-of-the-art knowledge tracing models (DKT, DKVMN, GKT) in contest performance prediction, achieving an F1-score of 0.807 and AUC of 0.841. The identified trajectory clusters also reveal pedagogically actionable insights for personalized intervention in programming courses.*

Key Words: Dynamic Time Warping, Educational Data Mining, Online Judge, Student Behavior Trajectory, Knowledge Tracing, Programming Education, Temporal Modeling, AC coding Dataset

1. INTRODUCTION

Online Judge (OJ) platforms have transformed programming education by enabling students to submit source code for automated evaluation and receive instant feedback. Unlike traditional educational scenarios, OJ platforms record rich multi-type feedback including Accepted (AC), Wrong Answer (WA), Time Limit Exceeded (TLE), and Compile Error (CE), among others [1]. These platforms generate longitudinal behavioral traces across months and years of student activity, offering unprecedented opportunities for Educational Data Mining (EDM) research.

A fundamental challenge in programming education analytics is characterizing how a student's learning behavior evolves over time. Most existing approaches including knowledge tracing models such as Deep Knowledge Tracing (DKT) [2], Dynamic Key-Value Memory Networks (DKVMN) [3], and Graph-based Knowledge Tracing (GKT) [4] model the knowledge state as a function of cumulative interaction history. While effective, these methods implicitly treat the temporal evolution of behavior as a secondary concern, focusing instead on predicting the correctness of the next submission. They fail to distinguish between a student who improves steadily and one who improves rapidly then stagnates two fundamentally different behavioral trajectories that demand different pedagogical interventions. Consider three hypothetical students, each with an identical final-week error rate of 0.20. Student A reduced their error rate monotonically from 0.80 over 12 weeks. Student B dropped from 0.80 to 0.22 in the first two weeks and remained flat thereafter. Student C oscillated between 0.60 and 0.30 across the semester before settling at 0.20. Standard static features cannot differentiate these students, yet their learning needs, risk profiles, and likely future performance differ substantially.

This paper addresses this gap by proposing DTW-TrajClust, a framework for temporal trajectory modeling of student programming behavior. Specifically, we: (1) construct weekly error-rate time series from raw OJ submission logs; (2) apply Dynamic Time Warping (DTW) as an elastic distance measure to compare trajectories of varying lengths; (3) use k-medoids clustering on the DTW distance matrix to discover trajectory archetypes; and (4) demonstrate that these trajectory features improve contest performance prediction significantly over static and existing knowledge-tracing baselines.

Our experiments are conducted on the publicly available AC coding dataset [5], a large-scale OJ dataset from Beihang University containing over four million submissions across six years. The trajectory clusters discovered are not only statistically robust but also pedagogically interpretable, providing actionable intelligence for educators.

2. LITERATURE REVIEW

2.1 Educational Data Mining in Programming

Ihantola et al. [6] provided a comprehensive literature review of EDM in programming education, noting the unique challenges posed by multi-type automated feedback and repeated submission behavior. Altadmri and Brown [7] analyzed 37 million compilations from novice programmers, identifying common error patterns but not their temporal evolution. Junior et al. [8] studied the impact of programming mistakes on student ability but used static per-assignment aggregates.

2.2 Knowledge Tracing Models

Piech et al. [2] introduced Deep Knowledge Tracing (DKT), applying recurrent neural networks to model knowledge state evolution from interaction sequences. Zhang et al. [3] proposed DKVMN, using memory-augmented neural networks to separate static concept storage from dynamic knowledge updates. Nakagawa et al. [4] introduced GKT, reformulating knowledge tracing as a time-series node classification task on a concept graph, achieving state-of-the-art performance on multiple benchmarks including the ACcoding OJ2019 subset. However, all these models operate on interaction sequences and do not explicitly model the temporal shape of behavioral evolution at the weekly or session level.

2.3 Temporal and Trajectory-Based Learning Analytics

Gao et al. [9] proposed cumulative prediction models across programming assignments but treated each assignment independently without modeling inter-week behavioral dynamics. Hoq et al. [10] demonstrated staged prediction of student performance in programming courses, showing that early-term data carries predictive power, but their features were static snapshots per stage. Bouallegue et al. [11] used static term-level features for performance prediction. In broader learning analytics, Jiang et al. [12] demonstrated that temporal evolution modeling substantially outperforms static snapshots in predicting student outcomes. Bettahi et al. [13] further confirmed this advantage using sequential models on MOOC data. The application of trajectory-shape modeling to coding-specific behavioral traces from OJ platforms, however, remains unexplored constituting the central contribution of this paper.

2.4 Dynamic Time Warping in Education

DTW was originally developed for speech recognition [14] and has since been applied in activity recognition, medical time series analysis, and gesture detection. Its elastic alignment property makes it particularly suitable for comparing time series of different lengths or with temporal distortions a natural fit for student learning trajectories where weeks of inactivity, exam periods, and course registration variation introduce temporal irregularities. To the best of our knowledge, DTW has not previously been applied to cluster student programming behavior trajectories from OJ platforms.

3. DATASET: ACCODING OJ PLATFORM

The Accoding dataset [5] is a large-scale, publicly available programming education dataset built from the ACcoding OJ platform at Beihang University. It contains 4,046,652 task-solving records submitted by 27,444 undergraduate students across 4,559 programming tasks over a span of six years (October 2015 to May 2022). Table 1 summarizes the dataset properties used in this study.

Table -1: ACcoding Dataset Summary

Property	Value	Used in Study
Total Students	27,444	3,650 (OJ2019)
Total Submissions	4,046,652	131,612 (OJ2019)
Programming Tasks	4,559	All tasks
Time Span	6 years (2015–2022)	Year 2019
Feedback Types	8 types	All 8 types
Trajectory Window	—	Weekly (W=7 days)

Each submission record contains: student ID, task ID, submission timestamp, programming language, source code length, time cost (ms), memory cost (KB), feedback type (AC/WA/TLE/MLE/RE/PE/CE/OE), and score. For temporal trajectory construction, we focus on the daily exercise subset of the OJ2019 partition, which contains 131,612 interaction records from 3,650 students the highest-density annual slice in the dataset. This partition was also used in prior knowledge tracing benchmarks [4], allowing direct comparison.

The feedback distribution in ACcoding is notably rich: AC submissions account for approximately 39.17% of all submissions, with WA being the most common non-correct outcome at 39.56%. This multi-type feedback structure provides a granular signal for trajectory construction beyond simple binary correct/incorrect encoding.

4. METHODOLOGY

4.1 Trajectory Construction

For each student s, we partition the academic year into weekly windows W = {w1, w2, ..., wT} where T is the number of active weeks for that student. Within each window wi, we compute the weekly error rate as:

ER(s, wi) = (Non-AC submissions in wi) / (Total submissions in wi)

This produces a scalar time series TS(s) = [ER(s,w1), ER(s,w2), ..., ER(s,wT)] for each student. Students with fewer than four active weeks are excluded to ensure trajectory meaningfulness, retaining 3,218 students for analysis. Weekly windows with zero submissions are treated as missing values and handled via linear interpolation before DTW computation.

4.2 Dynamic Time Warping Distance

Standard Euclidean distance is ill-suited for comparing time series of different lengths or with temporal phase shifts. DTW overcomes this limitation by finding an optimal elastic alignment between two sequences. Given two time series A = [a1,...,am] and B = [b1,...,bn], DTW computes the minimum-cost warping path through an m x n cost matrix D where D(i,j) = |ai - bj|^2 + min(D(i-1,j), D(i,j-1), D(i-1,j-1)). The DTW distance is D(m,n)^0.5. To prevent degenerate warping paths, we apply the Sakoe-Chiba band constraint with window size r = max(T) * 0.1.

DTW is particularly appropriate here because students may exhibit the same qualitative trajectory shape such as a steady decline in error rate but with different timings due to course enrollment patterns, personal schedules, or contest participation. DTW correctly identifies such students as behaviorally similar while Euclidean distance would not.

4.3 Trajectory Clustering via k-Medoids

We construct a pairwise DTW distance matrix of size 3,218 x 3,218 across all student trajectories. Since the DTW distance metric does not define a Euclidean embedding, we use k-medoids clustering (Partitioning Around Medoids, PAM) rather than k-means, as medoids are actual data points and are valid under any distance metric. The optimal number of clusters k is determined by evaluating the silhouette coefficient for k = 2 to 10. The silhouette analysis yields a peak at k = 5, which is adopted for all subsequent experiments.

The resulting cluster medoids serve as canonical trajectory prototypes and are used to characterize each student archetype. New students can be assigned to the nearest medoid trajectory using DTW distance, enabling real-time trajectory classification during the academic term.

4.4 Trajectory-Augmented Performance Prediction

To evaluate the predictive value of trajectory clusters, we frame contest performance prediction as a binary classification task: will a student achieve a pass rate above 0.5 in their next contest? For each student, we construct a feature vector comprising: (1) static features total submissions, overall AC ratio, number of contests entered, average task difficulty attempted; (2) trajectory features cluster assignment (one-hot, 5 dimensions), DTW distance to assigned medoid, trajectory slope (linear fit), and trajectory variance. A Random Forest classifier with 100 estimators is trained on 70% of students chronologically and evaluated on the remaining 30%, consistent with the data split used in prior Accoding studies [4].

5. EXPERIMENTAL RESULTS AND DISCUSSION

5.1 Identified Trajectory Archetypes

DTW k-medoids clustering with k=5 produced five trajectory archetypes summarized in Table 2. Each cluster exhibits a distinct behavioral signature with clear pedagogical implications.

Table -2: Trajectory Cluster Summary (OJ2019, n=3,218 students)

Cluster	Label	Avg. Init. ER	Avg. Final ER	Students (%)	Contest Pass Rate
C1	Steady Improvers	0.72	0.18	31.4%	0.74
C2	Early Plateauers	0.68	0.41	24.7%	0.49
C3	Struggle-Recovery	0.81	0.22	18.2%	0.68
C4	Chronic Stagnators	0.76	0.69	16.9%	0.29
C5	Volatile Learners	0.65	0.38	8.8%	0.44

Cluster C1 (Steady Improvers, 31.4%) represents the ideal learning trajectory a consistent monotonic decline in weekly error rate from approximately 0.72 to 0.18 over the academic year. These students show the highest contest pass rate (0.74) and form the largest single group. C2 (Early Plateauers, 24.7%) captures students who improve rapidly in the first four to six weeks but then stagnate. Their contest pass rate of 0.49 is notably lower than C1. C3 (Struggle-Recovery, 18.2%) identifies students who exhibit an initial increase in error rate followed by a strong recovery. Their final error rate (0.22) and contest pass rate (0.68) are nearly as good as C1, indicating resilience.

C4 (Chronic Stagnators, 16.9%) is the most educationally concerning cluster students whose error rate remains persistently high (0.69 at semester end) with the lowest contest pass rate (0.29). These students are at the highest risk of course failure and represent the primary target for early pedagogical intervention. C5 (Volatile Learners, 8.8%) shows irregular, oscillating trajectories without a clear trend, suggesting inconsistent study habits or external disruptions.

5.2 Prediction Performance Comparison

Table 3 compares DTW-TrajClust against a static feature baseline and three state-of-the-art knowledge tracing models on the contest performance prediction task.

Table -3: Model Comparison on Contest Performance Prediction (OJ2019)

Method	Acc.	Prec.	Recall	F1	AUC
Static Feature (Baseline)	0.711	0.698	0.703	0.700	0.731
DKT [2]	0.714	0.709	0.712	0.710	0.741
DKVMN [3]	0.738	0.731	0.734	0.732	0.762
GKT-MHA [4]	0.753	0.748	0.751	0.749	0.779
DTW-TrajClust (Proposed)	**0.812**	**0.806**	**0.809**	**0.807**	**0.841**

DTW-TrajClust achieves an F1-score of 0.807 and AUC of 0.841, outperforming all baselines. The static baseline (F1=0.700) confirms that aggregate features alone are insufficient. The margin over GKT-MHA (F1=0.749) the strongest knowledge tracing model on this dataset is 5.8 percentage points in F1, representing a substantial improvement. This gain is attributable entirely to the addition of trajectory shape features, which capture information that interaction-sequence models implicitly smooth over.

An ablation study confirms that removing trajectory cluster assignment from the feature set reduces F1 to 0.771, while removing DTW distance to medoid reduces F1 to 0.783 both below the full model. This validates that both the discrete cluster label and the continuous proximity measure contribute independently to prediction performance.

5.3 Pedagogical Implications

The trajectory archetypes identified have direct implications for educators using OJ platforms. Early identification of C4 (Chronic Stagnator) and C2 (Early Plateauer) students as early as week four of the semester when their trajectories become distinguishable enables timely intervention. A system built on DTW-TrajClust could flag at-risk students automatically, prompt instructors to provide additional scaffolding, or trigger adaptive task recommendations tailored to the student's trajectory profile. The C3 (Struggle-Recovery) archetype also demonstrates that initial difficulty is not necessarily predictive of eventual failure, cautioning against premature intervention that may undermine student autonomy.

6. CONCLUSIONS

This paper presented DTW-TrajClust, a temporal trajectory modeling framework for student programming behavior on Online Judge platforms. By applying Dynamic Time Warping to weekly error-rate time series extracted from the ACcoding dataset, we demonstrated that student behavioral trajectories cluster into five pedagogically meaningful archetypes Steady Improvers, Early Plateauers, Struggle-Recovery learners, Chronic Stagnators, and Volatile Learners that are not captured by existing static or knowledge-tracing approaches.

The proposed trajectory features significantly outperform state-of-the-art knowledge tracing models in contest performance prediction (F1=0.807, AUC=0.841), validating the central hypothesis that the temporal shape of learning behavior carries predictive information beyond cumulative interaction history. Future work will explore online trajectory classification during active semesters, integration with personalized learning path recommendation, and extension to multi-feedback-type trajectory vectors that incorporate WA, TLE, and CE rates as separate behavioral dimensions.

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