Learning Activity Trajectory Analysis for AAA 2013J

1. Overview

This report presents an initial trajectory analysis of student learning activity in AAA 2013J with the goal of informing practical, teacher-facing decision support. I wanted to see what students' learning paths look like—where they rise, where they fall, and how different these paths can be by aggregating and smoothing daily clickstream data.

As I examined the trajectories, I noticed that students begin separating into different patterns very early in the term, and these patterns stay stable throughout the course. Some students remain steady, some decline, and others work in bursts. Observing these early splits made me think about how teachers could use this information to identify who might need attention sooner and to anticipate periods where students may struggle. This work is an early step toward a more interpretable and actionable tool that could help teachers make sense of students' learning behavior over time.

The analysis focuses on three components:

A. Whole-class temporal dynamics
B. Distributional characteristics of activity over time (mean, variance, quantiles)
C. Behavioral clusters derived from time-series

Although the findings are preliminary, they suggest the potential value of trajectory-based analytics in understanding engagement rhythms, identifying at-risk patterns, and supporting teacher-facing tools.

2. Dataset & Preprocessing

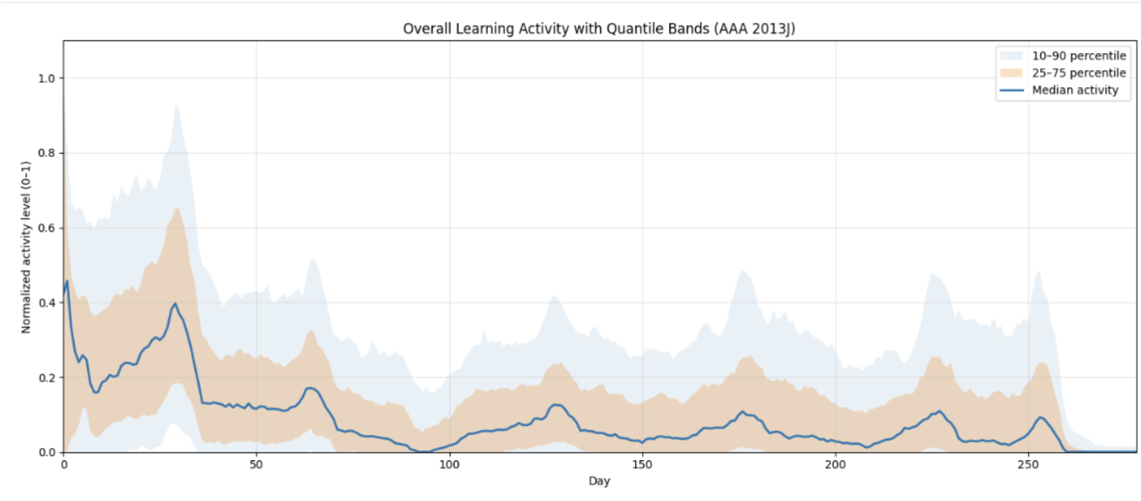
The analysis uses the AAA 2013J subset of the OULAD dataset, focusing primarily on the `studentVLE` table. The preprocessing steps were:

- **Filtering** AAA 2013J students using `studentInfo`.
- **Aggregating** daily VLE interactions (`sum_click`) for each student.
- **Realigning days** so the earliest interaction becomes day 0.
- **Smoothing** each student's daily activity using a 7-day rolling average to reduce noise caused by irregular login patterns.
- **Normalizing** each student's trajectory to a 0–1 scale to highlight behavioral patterns rather than raw click magnitude differences.
- **Clipping** extreme normalized values between 0 and 1.
- **Preparing** the smoothed-normalized matrix for visualization and clustering.

These steps allow the trajectories to be placed on the same scale so that patterns across students can be meaningfully compared.

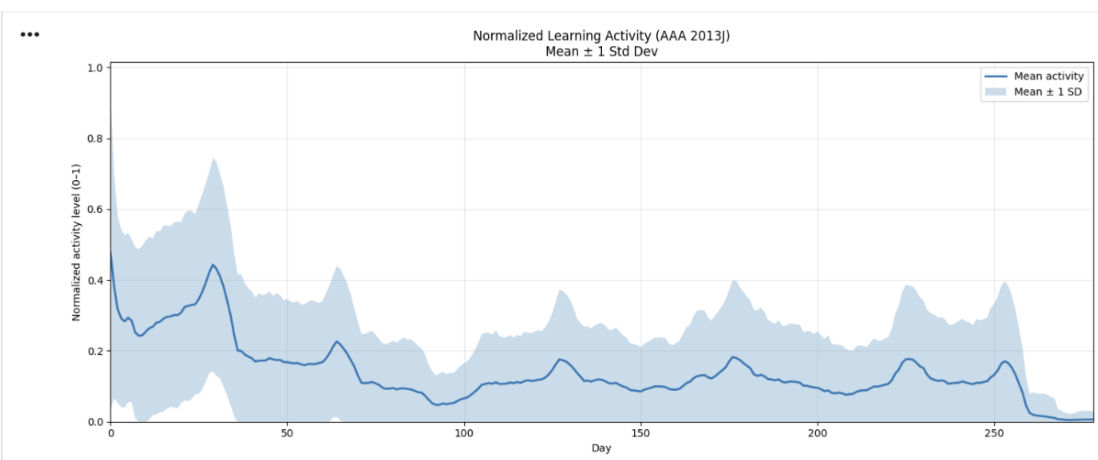
3. Results

3.1 Whole-Class Trajectory



- The class shows a sharp decline **in the first two weeks**, suggesting early-semester motivation fades quickly.
- The **median remains low and stable** afterward, indicating that most students engage lightly but regularly.
- The **10–90%** and **25–75%** bands widen mid-semester, meaning students become more differentiated as the course progresses.
- Occasional **mid-semester** spikes likely correspond to assessment deadlines or weekly cycles.
- The narrowing toward the end suggests **converging disengagement**, with many students reducing activity simultaneously

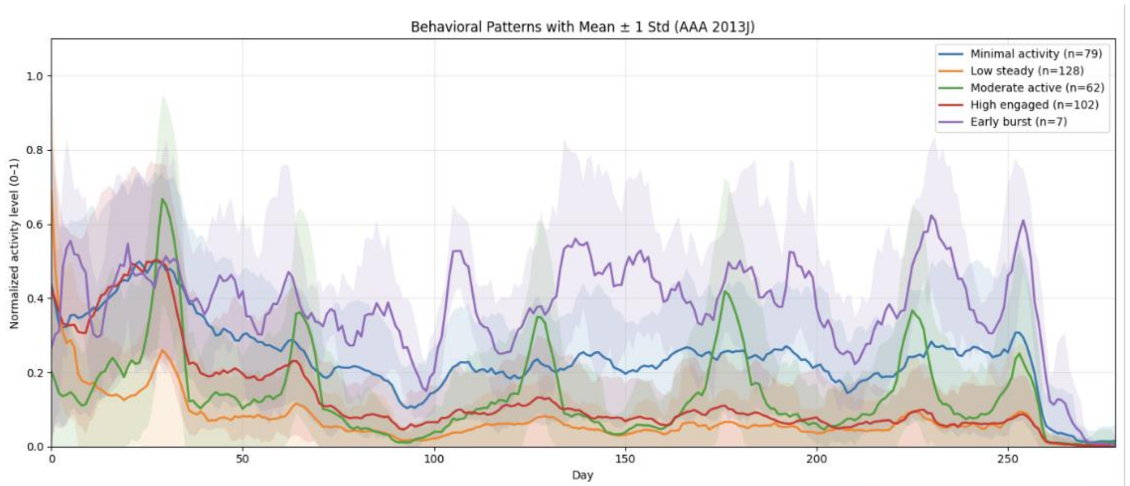
3.2 Mean ± Standard Deviation



- The mean reveals a **clear weekly oscillation pattern**, possibly reflecting submission cycles.

- Standard deviation increases around these peaks, meaning some students respond aggressively to deadlines while others do not.
- Activity decreases and flattens toward the end of the course, consistent with course structure winding down.
- Compared to the quantile plot, the mean curve hides subgroup differences, motivating clustering.

3.3 Behavioral Clusters



The k-means model (k = 5) produced distinct behavioral groups:

1. **Minimal activity**
   Flat, near-zero activity. Potential early-warning category.
2. **Low steady**
   Stable but low activity throughout the term.
3. **Moderate active**
   Moderate consistent engagement with some weekly structure.
4. **High engaged**
   Strong, rhythmic engagement patterns; likely high-performing students.
5. **Early burst**
   High activity in the first 1–2 weeks followed by steep decline;
   often corresponds to motivation drop or early overwhelm.

My Observation:
The early burst pattern seems particularly meaningful to students who start extremely active may be compensating for initial insecurity or may burn out early. This group could be important for targeted early-term intervention.

4. Potential Next Steps

• Based on the initial findings, I see a potential multi-stage direction for this work:

Stage 1 — Strengthen trajectory representations

- Experiment with different smooth windows.
- Add temporal features (burstiness, regularity, entropy).
- Validate the stability of clusters across preprocessing choices.

My current question:
Are early irregular patterns meaningful signals or just noise?

Stage 2 — Link behavior to outcomes

- Compare cluster membership with pass rates, withdrawal rates, and final grades.
- Identify which trajectory types correspond to risk.
- Evaluate whether early behavior (first 2–4 weeks) predicts final outcomes.

Why this matters:
It determines whether trajectories can support teachers in identifying students who may need help.

Stage 3 — Build an interpretable prototype tool

- Show individual trajectories.
- Display cluster patterns and typical vs. atypical behavior.
- Add simple early-warning score or thresholds.
- Allow teachers to view peaks, dips, and long-term trends.

Long-term direction:
A teacher-facing visualization system that aligns with LatrLab's emphasis on interpretation and human decision-making.

Appendix