Machine Learning for Education Laboratory
**ML4ED**

# Exploring Learning Profiles:
# Time Series Clustering Guided vs. Free Training

## On the Challenges of Identifying Learning Types in Calcularis

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## 1. INTRODUCTION + RESEARCH QUESTION

***Purpose:*** Identifying types of learners in guided versus free training.

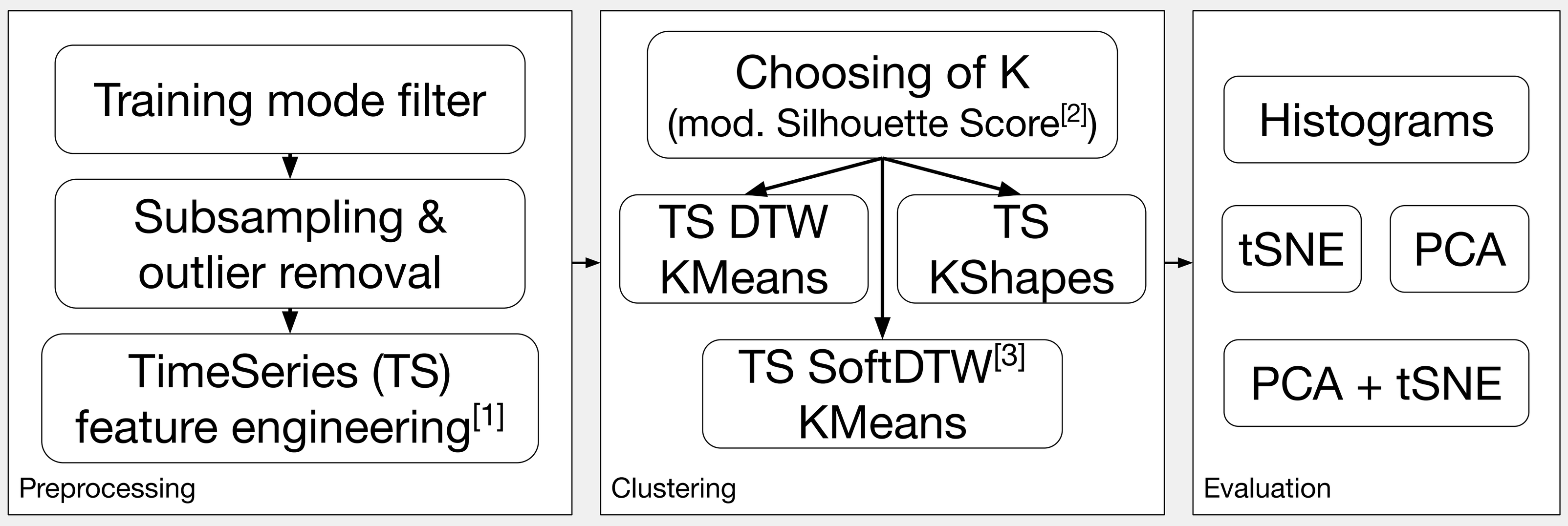
***Method:*** Multivariate K-Means time series clustering.

***Research question:*** Can time series clustering be used to identify types of learners and categorize them into different student profiles allowing for a comparison between guided and free training?

***Key takeaway:*** The identified clusters were largely overlapping, suggesting the used features may not be sufficient. While the current approach may not have been successful, a working pipeline for future research to build upon was created.

## 2. METHODOLOGY

### Model Architecture




### Dataset

| Engineered features |
|---|
| time_online |
| events_done |
| subtasks_done |
| Nb_of_different_games |
| correct |
| attempts_diff |

Strategies to cope with exponential computational cost of the models & metrics:

- Subsampling of the guided training dataset to train the model on 10 000 users only.
- Subsampling silhouette score averaged over multiple different runs.
- Removing of all outliers based on 3 standard deviations from the mean.


**Figure 1**. Guided training vs free training: games and user number comparison.

## 3. RESULTS

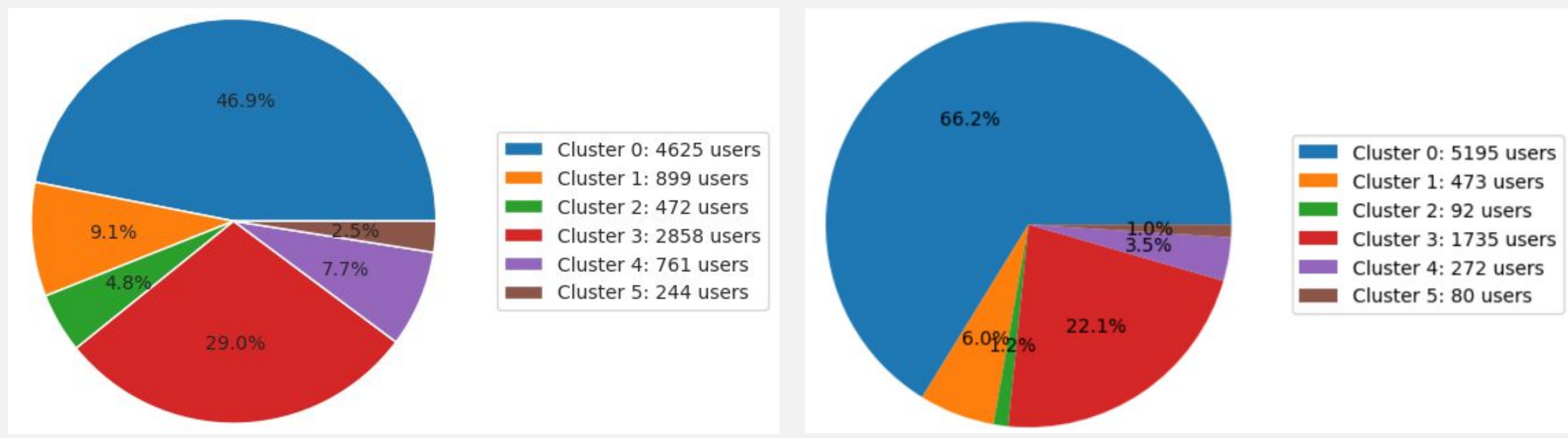



**Figure 2**. Left: Guided training with 9859 users sample and a silhouette score of 0.184
Right: Free training with 7847 users sample and a silhouette score of 0.386

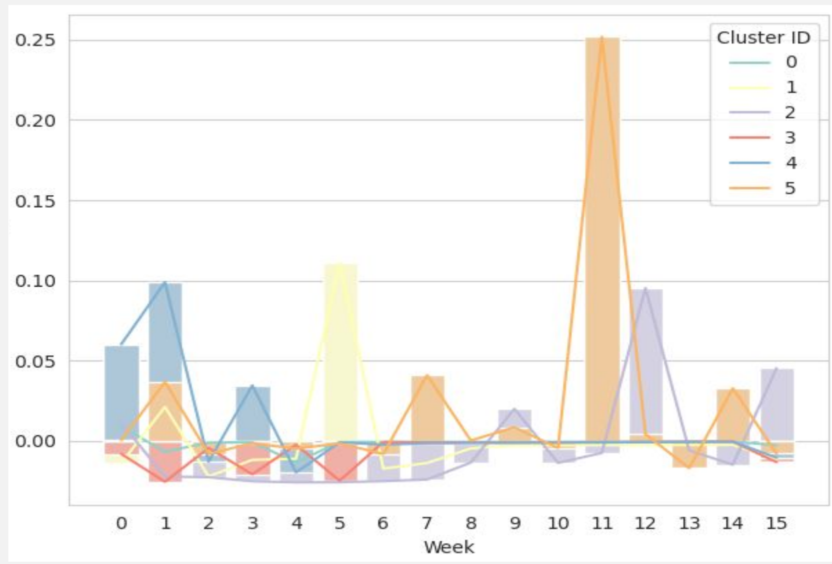



**Figure 3.** Plot of the online time feature cluster centroids for 16 weeks.

SoftDTW cluster centroids show different types of learners:

- Cluster zero clusters users that do not work much across all 16 weeks.
- In cluster three and four users seem to stop working after only a few weeks.
- Cluster two and five seem to work more between weeks 10 and 15 instead of more initially.

**Figure 4a**. Guided training

**Figure 4b**. Free training

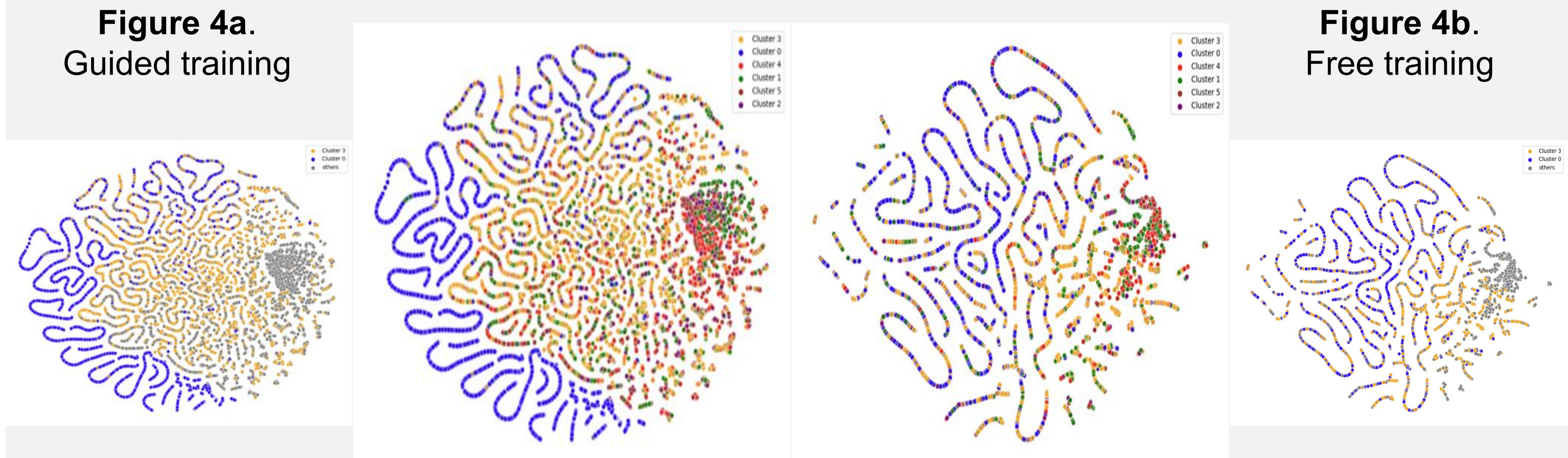


**Figure 4**. t-SNE plots of our clusters for different types of learners.
*Middle:* visualization of all six cluster; *Outsides:* visualization combining overlapping clusters.

## 4. CONCLUSION

- The **used features** for time series clustering **may not be sufficient** for identifying different types of learners.
- However, the study **provides a usable pipeline** to rerun the clustering approach with additional features in the future.
- Although **identified clusters overlap**, some **broad patterns** in student learning were **still recognizable**, suggesting that further exploration and feature refinement may lead to better differentiation.

## REFERENCES

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github.com/ML4BD/milestone-4-bd4ed