EPFL

Machine Learning for Education Laboratory
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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.

· why K means? which one didn't work
bc of computational constraints

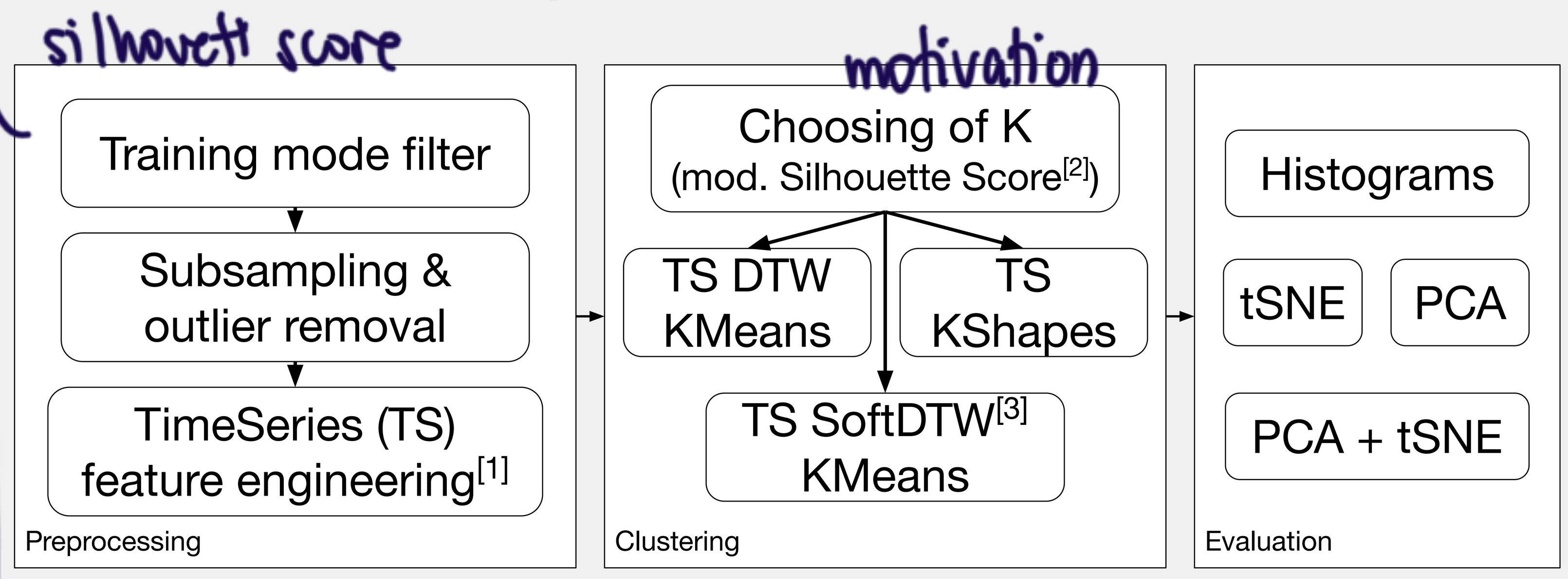
2. METHODOLOGY

- k is chosen to be 6 based on a modified silhouett score

+ modified silh. score

Model Architecture

motivation



Dataset

Engineered features
time_online
events_done
subtasks_done
Nb_of_different_games
correct
attempts_diff

Strategies to cope with the 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 all outliers based on three standard deviations from the mean.

• Feature engineering

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

• List features and invite listeners to ask about more concreteness

3. RESULTS

distribution of the clustering

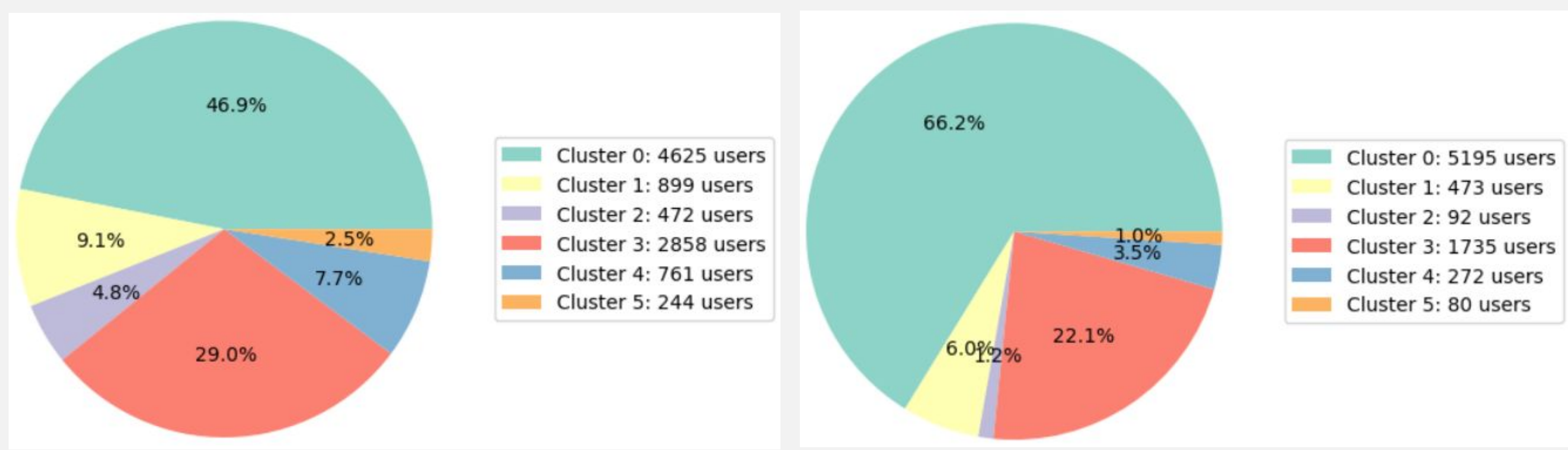


Figure 2. Left: Guided training with 9859 users sample and a silhouette score of 0.184
Right: Free training with 7847 users sample and a silhouette score of 0.386

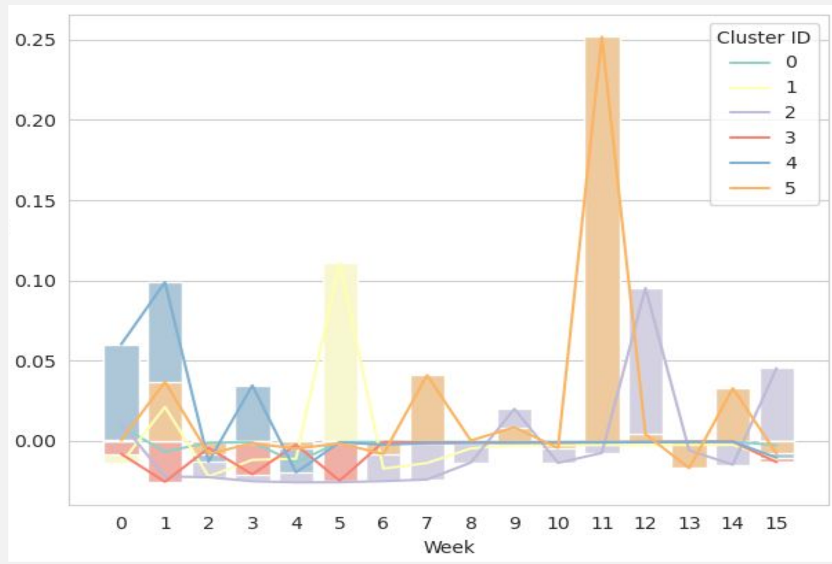


Figure 3. Plot of the online time feature cluster centroids for 16 weeks.

SoftDTW cluster centroids show different types of learners:

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

2&5: low at beg. & inconsistent at end

• cluster 0 = avg behavior
→ ⊕ diverse behaviors in GT
• 3 & 5: special early behavior (⊖, ⊖)

Figure 4a. Guided training

Figure 4b. Free training

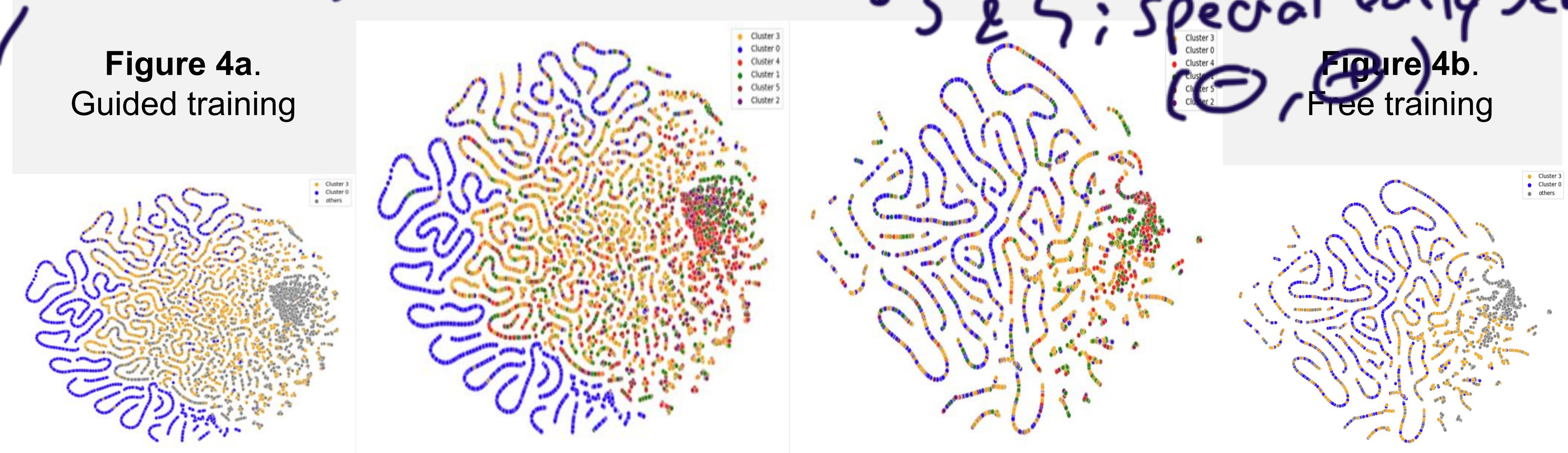


Figure 4. t-SNE plots of our clusters for different types of learners. *Middle:* visualization of all six clusters, *Outsides:* visualization combining overlapping clusters.

• describe features

clusters 0 & 3 = the less overlapping
↳ specially seen for outside tsne

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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