# AI based algorithms for teaching method selection: Using tandem learning in mathematics.

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## Abstract

### Background

The main objective of higher education institutions is to provide quality education to its students. One way to achieve this is is by introducing various teaching methods, one of which is tandem learning. Not everyone responds well to a one-size-fits-all method, and therefore, uncovering insights for predictive model selection tailored to individual students or classrooms becomes imperative for teaching institutions. The knowledge is hidden among the educational data set and is extractable through data mining techniques. The aim of this study was to evaluate the performance of machine learning algorithms for predicting student response to tandem learning.

### Methods

A sample of 89 high school students and 13 predictor variables has been used. The outcome of interest was a three state variable indicating whether the student responded well to implementation of tandem learning into education environment or not. In this paper, we implemented 9 classification machine learning algorithms that can be used to predict a target variable with three states and evaluated their performance with a 5 by 2-fold cross-validation with stratified folds.

### Results

Algorithm ... performed best with ... accuracy, f\_1 score ...

### Conclusion

The results imply that machine learning algorithms struggle to accurately predict students' responses to group learning in mathematics using the variables and sample size employed. As a result, they may not be appropriate for aiding teachers in making decisions about selecting teaching methods.

### Keywords

Assessment, education, machine learning, tandem learning, data mining, teching methods

### Math subject classification, MSC2020

97D40, 97D60, 62P99

## Introduction and theoretical framework

### Teaching methods and tandem learning

Critic of frontal teaching and new theoretical didactics, psychological, pedagogic, sociologic findings and positive experience in practical work have lead to the development of new indirect forms of education process (Blažič et al., 2003). Based on strong research literatures various forms of small-group learning are effective in promoting greater academic achievement, more favorable attitudes toward learning, and increased persistence through SMET courses and programs (Roschelle et al., 2010). Tandem learning is a special learning approach, where two students make an experiment together, formulate a report, solve a problem etc (Tomić 2002). It is a simple approach from organizational standpoint, as pair members have more chance for activity than in frontal teaching and group teaching, however they are not alone as in individual teaching method (Blažič et al., 2003).

Hundreds of studies have been conducted with main objective being being to determine the effects of cooperative learning on student achievement. We must keep in mind that this learning method is not only theoretical and a debate of research; it is used at some level by millions on teachers (Slavin et al., 2003) (v viru tudi dejanska cifra 81% v ameriki uciteljev to na dnevni ravni...). Many studies, which can be found in (Johnson & Johnson, 2011; Slavin, 1996; Webb, 1991) have found positive effect of for cooperative learning. (iz roschelle – tu notri tudi s kaksnim faktorjem posamezne raziskave)

Spremenljivke, ki vplivajo na delo v skupini – zakaj smo izbrali v raziskavi

By synthesizing these diverse factors, we can develop a more holistic framework for predicting the effects of tandem learning on student performance and tailor educational strategies accordingly.

From the above mentioned literature it might be understood that several factors impact the efficacy of working in small groups, such as tandem learning. For instance, students’ demographic characteristics (gender, age, class), teacher-related factors, and student-related factors (levels of mathematics anxiety, students’ personality, previous grade in mathematics) might have a non-negligible impact on predicting the efficacy of tandem learning in mathematics. Therefore, the aim of the present study is to investigate whether these factors can accurately predict the efficacy of tandem learning. To explore these influences, machine learning techniques might be applied.

### Machine learning and classification

Data mining is the process of uncovering hidden patterns, relationships, or insights within vast datasets through techniques from statistics and database management (Baradwaj & Pal, 2012). It involves data preprocessing to prepare information for analysis and utilizes methods such as clustering and association rule mining (Singhal & Jena, 2013). In contrast, machine learning, a subset of artificial intelligence, focuses on building predictive models by allowing computers to learn from data and make decisions or predictions (Candanedo et al., 2018). The sequences of steps identified in extracting knowledge from data is shown in Figure 2 below.

A black arrow pointing to a square

Description automatically generated

Figure : Knowledge discovery process

Machine learning encompasses various learning paradigms, including classification process and finds applications in areas like recommendation systems. Classification, a fundamental task in both data mining and machine learning, involves categorizing data into predefined classes, such as binary or three-state classification, based on patterns learned from labeled data. This classification process is employed in various domains, such as healthcare and sentiment analysis, to make data-driven decisions (Baradwaj & Pal, 2012). Goal of classification is to build a model based on input data, that explains said data. If we put new data in our model, the model outputs a solution based on input data it was built on. Usually, we have training data where are attributes and is a value of uknown function . Our goal is to find a function h that is the best approximation of function . Attributes (predictor variables) are independent (vectors), are target variables, function is called a model. Space of hypothesis expands very rapidly. If we have binary attributes, we would have different learning inputs and possible hypothesis. *To je bolj za v disertacijo kot za sam članek.*

Malo več o klasifikaciji ali ne? To je itak statistika, katere ne uvajamo v člankih, čeprav je tu bolj kompleksna?

### Connecting tandem learning and machine learning

Technologies can be considered in terms of whether they are mainly student teaching (with primarily instructionist approach), student supporting (primarily constructivist approach), or teacher supporting (which primarily help teachers do tasks they already do but faster or with less effort) (Holmes et al., 2019).

Beyond its broader applications, machine learning has been harnessed to predict student performance with remarkable precision (Ofori et al., 2020; Qazdar et al., 2019; Rastrollo-Guerrero et al., 2020; Yakubu & Abubakar, 2022). Leveraging the power of data analytics and advanced algorithms, machine learning models have been applied to forecast student success (Yakubu & Abubakar, 2022), identify at-risk learners (Adnan et al., 2021; Chui et al., 2020), and tailor educational interventions (Luan & Tsai, 2021; Stimpson & Cummings, 2014; Tsai et al., 2020; Yang, 2021). This transformative application of machine learning is exemplified by research conducted by Siemens & Gasevic (2012), which introduced the concept of "learning analytics" and demonstrated its potential in predicting student outcomes, which was demonstrated also by other studies (Abana, 2019; Bhusal, 2021; Cortez & Silva, 2008; Kotsiantis et al., 2004; Minaei-Bidgoli et al., 2003). Aside from forecasting success, machine learning can help us identify the most important variables that affect said forecast (Lu et al., 2020; Luan & Tsai, 2021). Multiple studies have dvelved into the analysis of crucial features in learning enviroment (Hodges, 2018; Humphrey et al., 2009; Moradi et al., 2018; Scribner & Donaldson, 2001), however only few have harnessed the power of modern algorithms, such as machine learning, which hold the potential for significantly enhanced sight. Therefore, it is of paramount importance to explore in great detail the feature selection problem.

## Empirical work

Research was conducted as he effectiveness of tandem learning in high school mathematics remains unclear due to the complexity of numerous variables influencing its success.

This study aims to leverage three state classification machine learning algorithms to analyze multifaceted variables to determine successfulness of tandem learning enviroment.

Given the scarcity of comprehensive studies employing machine learning algorithms to assess teaching method selections, this research acknowledges the potential limitations in drawing definitive conclusions. While aiming to discern patterns of predicting successfulness of tandem learning enviroment, this study will consider the need for cautious interpretation of results. Even in the absence of conclusive findings, insights gathered from the analysis will contribute to the ongoing discourse on the efficacy of tandem learning in mathematics education. Therefore we hypothesize that even when feeding machine learning models with diverse data sets encompassing student profiles and collaborative dynamics some algorithms will perform sub par, while others may perform fair.

## Methodology

In the present research, the causal descriptive method of pedagogical research is applied.

## Sample

We used a dataset gathered at a high school in Slovenia, which is pulicly available at (Bregant, 2023). Sample comprised of 89 11th and 12th grade of a Slovenian Gymnasium (i.e., high school). We chose ... predictor variables out of 13, based on mutual information score (cite). All variables provided were used.... Internal consistency of a dataset was already performed at (Bregant et al., 2024), with McDonal's Omega for continuous data and Gutman's Lambda for categorical variables, them measuring 0.54 and 0.45 perspectively.

## Data preprocessing and data analysis

The gathered data was analysed using Python programming language, primarily using pandas (version 2.1.3) and scikit-learn (version 1.3.2) libraries. Machine learning code, as well as variable importance and other data analysis notebooks are openly accessible at (Bregant, 2023)

Dataset was already in the form of tidy data (Wickham, 2014). Categorical variables, which were a priori encoded using label encoding were transformed into dummy variables using one-hot as most machine learning algorithms require numerical input and do not handle well numerical data, that is not continuous (Tan & Pu, 2023; Wu et al., 2020).

We implemented N ML algorithms: Naive Bayes, K-Nearest Neighbors, Decision Tree, Gaussian Mixture, Linear Discriminant Analysis, Ada Boots (with 100 estimators), Gradient Boosting (with 100 estimators), Support Vector Machine (with RBF kernel) and Random Forest (with 100 estimators). Said algorithms are capable of performing 3 state classification. Models were evaluated using 5x2-CV with stratified folds with the main metric of performance evaluation being average F1-score? through average fold repetition.

## Results

### Student sample

> Class=1 : 6/89 (6.7%)

> Class=2 : 39/89 (43.8%)

> Class=3 : 44/89 (49.4%)

### Model performance

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Classifier | Accuracy | Precision | Recall | F1-score |
| Naive Bayes | 0.338 | 0.272 | 0.377 | 0.258 |
| K-Nearest Neighbors | 0.505 | 0.344 | 0.361 | 0.343 |
| Decision Tree | 0.493 | 0.394 | 0.354 | 0.334 |
| Gaussian Mixture | 0.144 | 0.074 | 0.178 | 0.076 |
| Linear Discriminant Analysis | 0.450 | 0.328 | 0.381 | 0.311 |
| AdaBoost | 0.484 | 0.307 | 0.350 | 0.316 |
| Gradient Boosting | 0.505 | 0.369 | 0.368 | 0.344 |
| Support Vector Machine | 0.450 | 0.159 | 0.304 | 0.208 |
| Random Forest | 0.505 | 0.302 | 0.367 | 0.318 |

A group of blue squares

Description automatically generated

## Discussion

…

## Conclusions and limitations

Study does not include a prediction whether tandem learning is overall effective or not. It simply includes information about predicting certain student performance, which is a limitation.

Some authors have suggested that students should not be forced to use learning approaches that do not suit their cognitive style.

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