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

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## Abstract

### Background

The main objective of highereducation 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 75 high school students and 14 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. N\_2 predictor variables were selected using mutual information score with the outcome. In this paper, we implemented N\_3 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 Spremljanje pouka, Ljubljana: preveri se enkrat ali je direkt citat ali povzeto). 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.

### 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. 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. The sequences of steps identified in extracting knowledge from data is shown in Figure 2 below.

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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

Let us briefly discuss where AI is used in education today. We will focus mainly on the use of AI to support learning (student and teacher facing AI). 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. Leveraging the power of data analytics and advanced algorithms, machine learning models have been applied to forecast student success, identify at-risk learners, and tailor educational interventions. 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. Through this introduction, we will delve into the specific ways in which machine learning is harnessed to predict student performance and its profound implications for the education sector. Some other examples of predicting student performance with different metrics and models can be found in (Abana, 2019; Bhusal, 2021; Cortez & Silva, 2008; Kotsiantis et al., 2004; Minaei-Bidgoli et al., 2003).

## Empirical work

## Methodology

In the present research, the causal non-experimental method of pedagogical research is applied.

## Sample

We used a dataset gathered at a high school in Slovenia, which is pulicly available at (Bregant) (accesed at ...). Sample comprised of ... 11th and 12th grade of a Slovenian Gymnasium (i.e., high school). We chose ... predictor variables out of ..., based on mutual information score (cite). As described in table ..., the important variables turned out to be ... (cite).

## Data preprocessing and data analysis

The gathered data was analysed using Python programming language, primarily using pandas and scikit-learn libraries.

Dataset was already in the form of tidy data (Wickham, Bregant). 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 output variables (CITAT) and do not handle well numerical data, that is not continuous (CITAT).

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 (citat zakaj to dobro) with the main metric of performance evaluation being average F1-score? through average fold repetition.

## Results

### Student sample

Statističen opis kakšen je bil vzorec (intervali zaupanja za npr. cilnje spremenljivke, …). MBTI vzamemo zvezne spremenljivke, ki normalizira podatke, ki bi sicer implicirali bipolarnost ljudi. (Ramsay).

> Class=1 : 5/76 (6.6%)

> Class=2 : 34/76 (44.7%)

> Class=3 : 37/76 (48.7%)

### Model performance

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Classifier | Accuracy | Precision | Recall | F1-score |
| Naive Bayes | 0.346 | 0.337 | 0.425 | 0.292 |
| K-Nearest Neighbors | 0.447 | 0.286 | 0.315 | 0.295 |
| Decision Tree | 0.398 | 0.268 | 0.281 | 0.268 |
| Gaussian Mixture | 0.187 | 0.122 | 0.180 | 0.101 |
| Linear Discriminant Analysis | 0.463 | 0.327 | 0.337 | 0.313 |
| AdaBoost | 0.356 | 0.242 | 0.254 | 0.236 |
| Gradient Boosting | 0.460 | 0.315 | 0.329 | 0.318 |
| Support Vector Machine | 0.461 | 0.236 | 0.318 | 0.250 |
| Random Forest | 0.527 | 0.356 | 0.378 | 0.348 |

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Description automatically generated

Table : Related feature variables

|  |  |  |  |
| --- | --- | --- | --- |
| Variable | Description | Possible values | Variable type |
| Gender |  | 0-1 (Male, female) | A priori state |
| Class |  | 0-6 (7 present classes) | A priori state |
| Teacher |  | 0-3 (4 teachers) | A priori state |
| Previous grade |  | 1-5 | A priori state |
| Extroversion score | From online test:  (intercitat) | 0-1 (with 0.01 step) | Psychological background |
| Sensing / intuition | From online test:  (intercitat) | 0-1 (with 0.01 step) | Psychological background |
| Thinking / feeling | From online test:  (intercitat) | 0-1 (with 0.01 step) | Psychological background |
| Judging / perceiving | From online test:  (intercitat) | 0-1 (with 0.01 step) | Psychological background |
| Qualitative interaction |  | 1-3 (little communication – lot of communication) | Tandem learning |
| Quantitative interaction |  | 1-3 (work was not productive - ???) | Tandem learning |
| Outperforming partner |  | 1-3 (worked less – outperform) | Tandem learning |
| Teacher presence |  | 1-3 (present a little – present a lot) | Tandem learning |

Table : Head of dataset

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Student number | Performance | Gender | Class | Teacher | Extroversion score | ... | Teacher presence |
| 0 |  | M | 3B |  | 86 |  |  |
| 1 |  | F | 3B |  | 76 |  |  |
| .. |  |  |  |  |  |  |  |

## 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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## References

Abana, E. C. (2019). A Decision Tree Approach for Predicting Student Grades in Research Project using Weka. *International Journal of Advanced Computer Science and Applications*, *10*(7). https://doi.org/10.14569/IJACSA.2019.0100739

Baradwaj, B. K., & Pal, S. (2012). *Mining Educational Data to Analyze Students’ Performance* (arXiv:1201.3417). arXiv. https://doi.org/10.48550/arXiv.1201.3417

Bhusal, A. (2021). *Predicting Student’s Performance Through Data Mining*. https://doi.org/10.48550/ARXIV.2112.01247

Blažič, M., Ivanuš-Grmek, M., Kramar, M., & Strmčnik, F. (2003). *Didaktika: Visokošolski učbenik*. Visokošolsko središče, Inštitut za raziskovalno in razvojno delo.

Cortez, P., & Silva, A. (2008). *Using data mining to predict secondary school student performance*.

*Fastest Myers-Briggs test*. (n.d.). Retrieved 21 October 2023, from https://dynomight.net/mbti/

Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial Intelligence in Education. Promise and Implications for Teaching and Learning.*

Johnson, D. W., & Johnson, R. T. (2011). *Learning together and alone: Cooperative, competitive, and individualistic learning* (5. ed. [Repr.]). Allyn and Bacon.

Johnson, D. W., Johnson, R. T., & Smith, K. A. (1991). *Cooperative learning: Increasing college faculty instructional productivity*. School of Education and Human Development, George Washington University.

Kotsiantis, S., Pierrakeas, C., & Pintelas, P. (2004). Predicting students’ performance in distance learning using machine learning techniques. *Applied Artificial Intelligence*, *18*(5), 411–426. https://doi.org/10.1080/08839510490442058

Kubale, V. (2015). *Skupinska učna oblika* (2. dopolnjena izd). Samozal. V. Kubale ; Piko’s Printshop.

Minaei-Bidgoli, B., Kashy, D. A., Kortemeyer, G., & Punch, W. F. (2003). Predicting student performance: An application of data mining methods with an educational web-based system. *33rd Annual Frontiers in Education, 2003. FIE 2003.*, *1*, T2A\_13-T2A\_18. https://doi.org/10.1109/FIE.2003.1263284

*Myers-Briggs/Jung Test: Open Extended Jungian Type Scales*. (n.d.). Retrieved 21 October 2023, from https://openpsychometrics.org/tests/OEJTS/

Nunar, N. (2020). *Izzivi skupinskega dela učencev* [Master’s thesis, Univerza na Primorskem]. https://repozitorij.upr.si/IzpisGradiva.php?lang=slv&id=12851

Peklaj, C. (2001). *Sodelovalno učenje ali Kdaj več glav več ve* (1. izd., 1. natis). DZS.

Puklek, M. (2001). Skupinsko delo: Kako ga oceniti? *Didakta*, *11*(60/61), 47–51.

Ramsay, A., Hanlon, D., & Smith, D. (2000). The association between cognitive style and accounting students’ preference for cooperative learning: An empirical investigation. *Journal of Accounting Education*, *18*(3), 215–228. https://doi.org/10.1016/S0748-5751(00)00018-X

Roschelle, J., Rafanan, K., Bhanot, R., Estrella, G., Penuel, B., Nussbaum, M., & Claro, S. (2010). Scaffolding group explanation and feedback with handheld technology: Impact on students’ mathematics learning. *Educational Technology Research and Development*, *58*(4), 399–419. https://doi.org/10.1007/s11423-009-9142-9

Siemens, G., & Gasevic, D. (2012). Guest Editorial—Learning and Knowledge Analytics. *Educational Technology and Society*, *15*(1–2).

Slavin, R. E. (1996). Research on Cooperative Learning and Achievement: What We Know, What We Need to Know. *Contemporary Educational Psychology*, *21*(1), 43–69. https://doi.org/10.1006/ceps.1996.0004

Slavin, R. E., Hurley, E. A., & Chamberlain, A. (2003). Cooperative Learning and Achievement: Theory and Research. In I. B. Weiner (Ed.), *Handbook of Psychology* (1st ed., pp. 177–198). Wiley. https://doi.org/10.1002/0471264385.wei0709

Webb, N. M. (1991). Task-Related Verbal Interaction and Mathematics Learning in Small Groups. *Journal for Research in Mathematics Education*, *22*(5), 366. https://doi.org/10.2307/749186