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Tracking and forecasting of students' progress using Multiple-Criteria Decision Making and kNN methods

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1. INTRODUCTION

A problem in higher education related to tracking and forecasting students' progress and exam performance has been discussed. During the semester, every student would benefit from information about whether their work on the course is sufficient to achieve the desired result on the final exam. If it was pointed out to them at the right moment that success in the subject is likely to be absent, it could encourage them to increase efforts for the rest of the semester and thus in the end achieve their goal. However, if a bad result is expected for most participants, a change in the teaching method should be considered. That is why two objectives were set in the research.

2. OBJECTIVES

- Determine the moment during the semestar when it can be predicted that the student will not successfully complete the course.
- Check whether the teaching methods are appropriate through the success of parts or whole group.

3. METHODS

To give advice to the student at certain moments during the semestral course, it is necessary to determine the level of their knowledge and then make a forecast of the expected result on the exam. At five time points (t_2,...,t_6) student knowledge is assessed using the MCDM method - PROMETHEE II, which takes into account four criteria (attendance, activity, homework, and test), and teacher preferences given by preference functions (Table 1).

Students' achievements are categorized through grades based on the results of the PROMETHEE II method in milestones t_2 - t_6. The k-nearest neighbors (kNN) algorithm was used for grades classification. The classification is based on MCDM results in two sets of input variables (T3, T4, T5) and (T2, T3, T4, T5, T6). The target variable is the student's grade ranging from 5 (failing) to 10 (excellent).

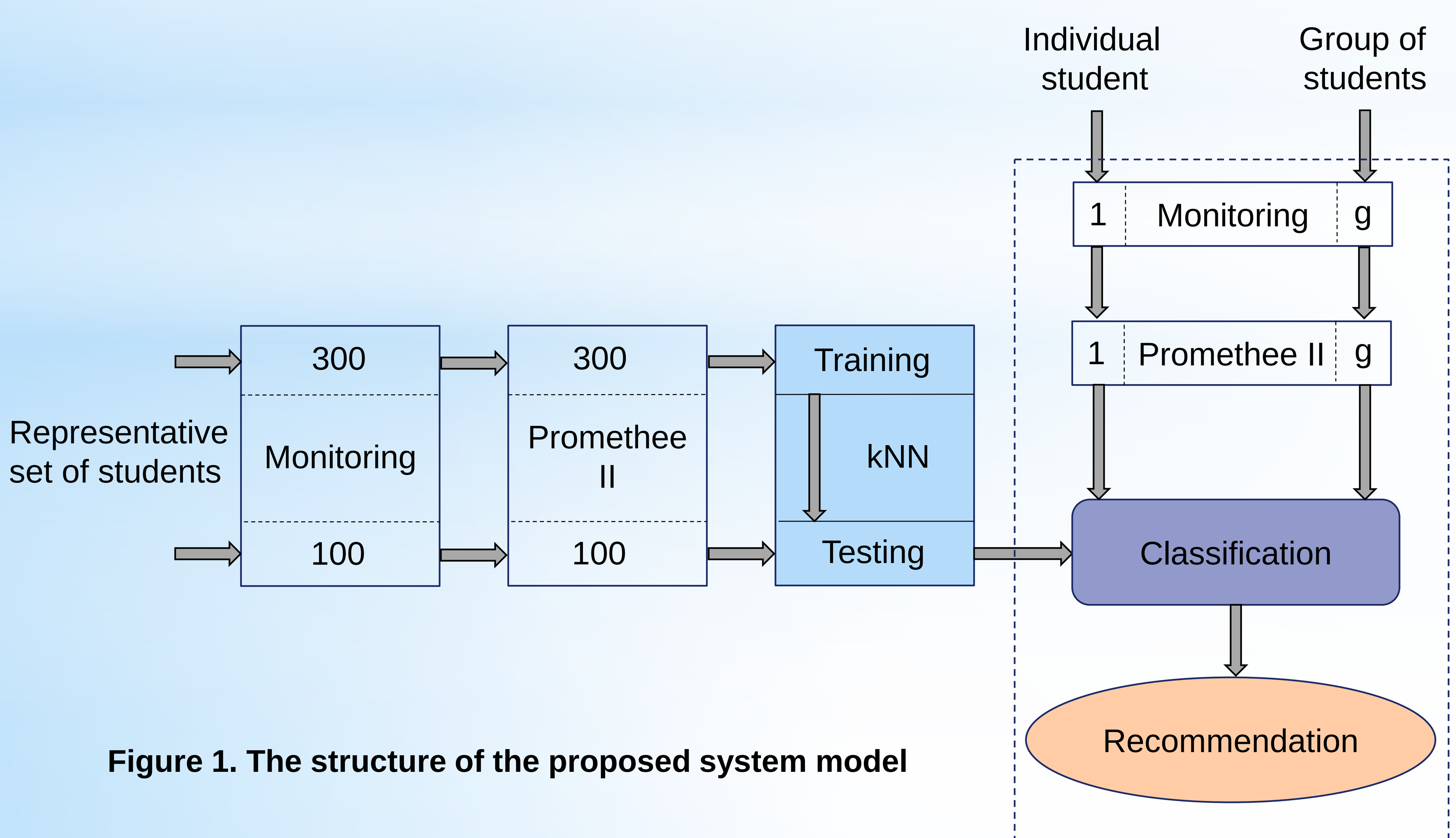

Figure 1. The structure of the proposed system model

Table 1. PROMETHEE II: input data transformation by prereference functions (PF)

Criterion	PF	Layout	t1	t2	Weigth
Attendance	Level		0.2	0.8	0.5
Activity	Level		0.5	1.5	1
Homework	V-Shape		7	-	2.5
Test	Gaussian		5	-	5

4. RESULTS and DISCUSSION

Accuracy:

- Depending on the input variables accuracy was 80-92%.
- There was no deviation of more than one grade.
- Forecasts based on the input variables T2-T6 in the test set were accurate 100% in grades 5 and 10. However other final grades from 6 to 9 are mainly overestimated.
- The application of the PROMETHEE II method followed by the kNN classifier can be very useful in monitoring student achievements.

Implications:

- Productive teaching strategies and supportive environments. Specifically supporting student-centered instruction and the formation of learning communities in the classroom.
- The lecturer is enabled to point out in time to the student which segment of the work needs to be improved in order to achieve the desired final result in the course.
- By predicting students' grades before the final exam, they can take significant steps to improve their performance.
- If the results obtained at the group level at some point deviate from the expectations, this would indicate to the lecturer that the current teaching methods should be changed or adjusted.
- Enabling a fair evaluation of the student's achievements through the final grade, taking into account their overall activity and work results during the semester course, especially in distance learning in online and combined learning.

Table 2. Classification table kNN

kNN	Training	Predicted grade						Correct classification	Test	Predicted grade						Correct classification
Input variables	Observed	5	6	7	8	9	10		Observed	5	6	7	8	9	10	
T2, T3, T4, T5, T6	5	20	3	0	0	0	0	87.0%	5	7	0	0	0	0	0	100.0%
	6	2	80	3	0	0	0	94.1%	6	0	23	1	0	0	0	95.8%
	7	0	4	59	5	0	0	86.8%	7	0	1	24	4	0	0	82.8%
	8	0	0	4	54	0	0	93.1%	8	0	0	0	19	1	0	95.0%
	9	0	0	0	5	32	1	84.2%	9	0	0	0	0	10	1	90.9%
	10	0	0	0	0	3	25	89.3%	10	0	0	0	0	0	9	100.0%
	Overall %	7.3%	29.0%	22.0%	21.3%	11.7%	8.7%	90.0%	Overall %	7%	24%	25%	23%	11%	10%	92.0%
T3, T4, T5	5	18	5	0	0	0	0	78.3%	5	6	1	0	0	0	0	85.7%
	6	2	77	6	0	0	0	90.6%	6	0	22	2	0	0	0	91.7%
	7	0	8	53	7	0	0	77.9%	7	0	2	21	6	0	0	72.4%
	8	0	0	9	46	3	0	79.3%	8	0	0	2	16	2	0	80.0%
	9	0	0	0	9	23	6	60.5%	9	0	0	0	1	8	2	72.7%
	10	0	0	0	0	5	23	82.1%	10	0	0	0	0	2	7	77.8%
	Overall %	6.7%	30.0%	22.7%	20.7%	10.3%	9.7%	80.0%	Overall %	6%	25%	25%	23%	12%	9%	80.0%

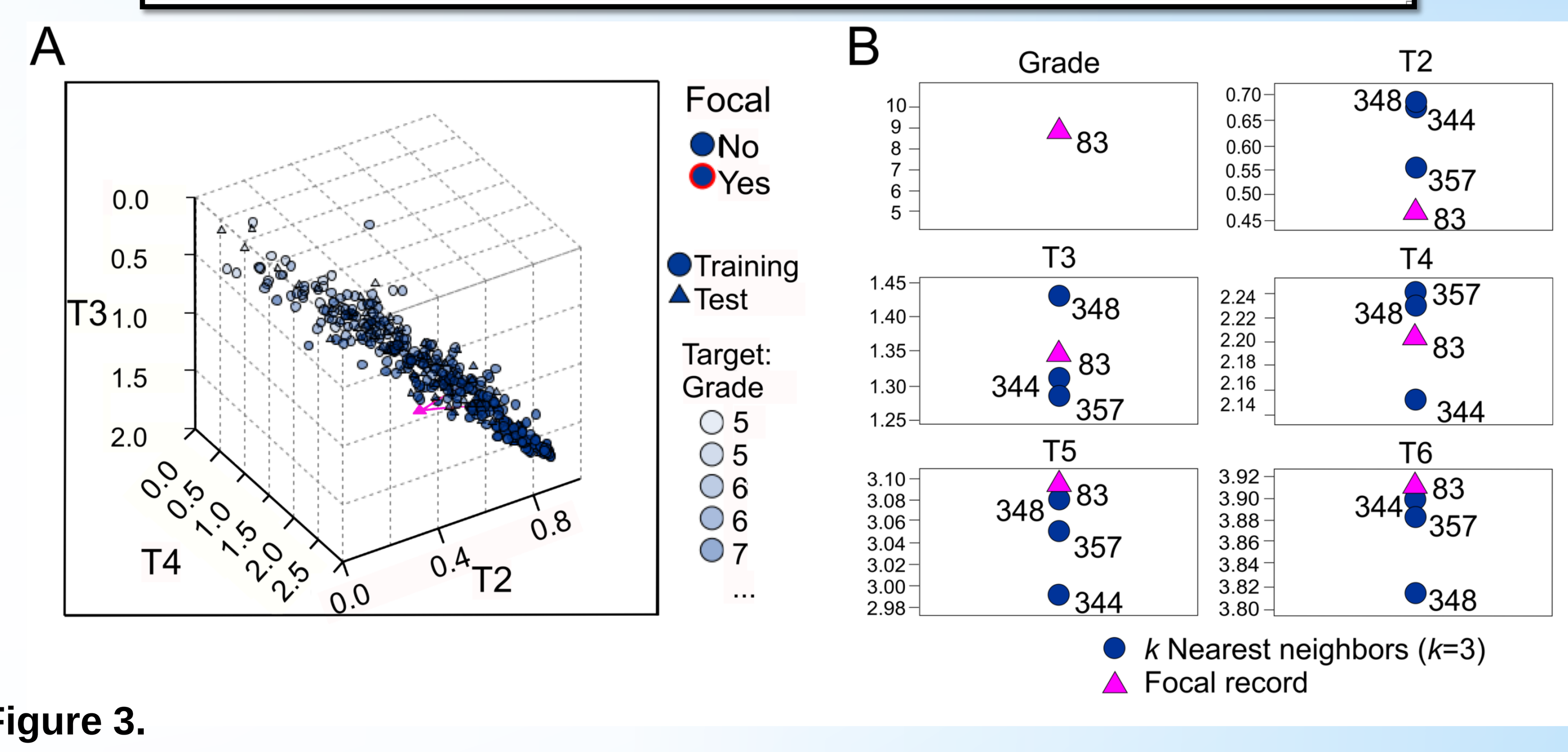

Figure 3.

A. Three-dimensional projection of the 5-dim predictor space representing training and test sets. The Magenta triangle represents the focal case (student #83) connected to its three nearest neighbors.

B. The final grade (9) of the student #83 and the peer's charts with 3 nearest neighbors in milestones T1-T6.

5. CONSLUSIONS

- Tracking student progress throughout the course allows predicting outcomes
- Student progress is based on attendance at classes, activities, homework, and tests
- Monitoring during the course encourages student engagement and progress
- Early detection of risk for poor outcomes allows changing the teaching strategy
- Predicting and fair evaluation of student achievement through final assessment

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