DATA MINING FOR SMALL STUDENT DATA SET – KNOWLEDGE MANAGEMENT SYSTEM FOR HIGHER EDUCATION TEACHERS

Srečko Natek
International School for Social and Business Studies, Slovenia
srecko.natek@vizija.si

Moti Zwilling
College of Law and Business, Israel
motiz@clb.ac.il

Abstract:
Higher education teachers are often curious whether students will be successful or not. Before or during a course they try to estimate the percentage of successful students. But is it possible to predict the success rate of students enrolled in their course? Are there any specific student characteristics, known to a teacher, which can be associated with the student success rate? Is there any relevant student data available to teachers on the basis of which they could predict the student success rate? The answers to the above research questions can generally be obtained with data mining tools. Unfortunately, data mining algorithms work best with large data sets, while student data, available to higher education teachers, is extremely limited and clearly falls into the category of small data sets. Thus, the study focuses on data mining for small student data sets and aims to answer the above research questions using data and comparative analysis using data mining tools normally available to higher education teachers. The conclusions of this study are very promising and will encourage teachers to incorporate data mining tools as an important part of their higher education knowledge management systems.

Keywords: data mining, knowledge management system, predicting student's success rate, small data set

1. DATA MINING FOR SMALL DATA SET AS PART OF HIGHER EDUCATION TEACHER'S KNOWLEDGE MANAGEMENT SYSTEM

In knowledge management process, data mining technique can be used to extract and discover the valuable and meaningful knowledge from a large amount of data. Nowadays,data mining has given a great deal of concern and attention in the information industry and in society as a whole. This technique is an approach that is currently receiving great attention in data analysis and it has been recognized as a newly emerging analysis tool (Osei-Bryson, 2010; Park, 2001; Sinha, 2008; Tso & Yau, 2007; Wan, 2009; Zanakis, 2005;Zhuang et al., 2009).

There are many areas which adapted this approach to solve their problems such as in finance, medical, marketing, stock, telecommunication, manufacturing, health care, customer relationship and etc. However, the data mining application has not attracted much attention from people in relation to Educational Systems.

In particular, Data mining become very popular among researches because so many standalone or desktop data mining tools are available e.g. Microsoft Excel, SPSS, Weka, Protégé as Knowledge Acquisition System and Rapid Miner. Higher education institutions promote knowledge management as incentive environment for their teachers (e.g. Gomezelj & Biloslavo & Trnavčević, 2010, p. 49).

So data mining is recognized as contemporary tool for building knowledge management systems (Jashapara, 2011 pp. 204 - 206). A knowledge management approach to data mining process, otherwise associated with business intelligence technology, brings some new sinergy and added value to data mining solutions (Wang & Wang, 2008, pp. 622 – 630). This study was focused on higher education teacher's knowledge management systems as part of theirs educational and research work. Unfortunately most data mining technique work best with very large samples. Andonie, reported that some data mining technique, e.g. neural networks may not be able to accomplish the learning task as small datasets cannot provide enough data to fill the gaps between too small samples (Andonie, 2010, pp. 282 – 283). Several authors conclude that small datasets limit the scope of data mining technique (Yuan & Fine, 1998, pp. 266 – 268).

In real-life there are many situations, where relatively small data sets are normal, at least from the point of view of users. The student's data of one course are good example of such situation. Even if the course attend relatively large group of students the relevant data are considered to be small dataset.

Andonie even suggested that there is no universal optimal solution to the problem of small datasets (Andonie, 2010, pp. 283). So what possibilities are available to the higher education teachers if they want to explore how the new course's students will be successful, using contemporary but available data mining tools. Student's data, available to higher education teachers are extremely limited and clearly fall into the category of small data set. Nevertheless the research follows the "induction learning rules from examples" as one of the primary characteristics of machine learning (Becerra & Gonzales & Sabherwal, 2004, p. 220). Described approach is very popular and well supported by data mining tools, used in the study.

The research goal is to focus on small student data set data mining, trying to answer various teacher's questions, using the data and data mining tools, normally available to average higher education teachers. For higher education teachers the most important outcome are relatively reliable students' success prediction and user friendly experience. Bukowitz and Williams (Bukowitz &Williams, 2000, p. 5) advocate how technology is blurring the distinction between types of knowledge from unknown knowledge to known knowledge. The study supports their conceptual model as data mining on students data sets discovered some interesting key influencer and "Final grade" prediction.

2. BUILDING STUDENT DATA MINING MODEL

2.1 Building student data mining model for MS Excel Table Tools data mining

Several authors suggest different steps for building data mining model, focusing mainly on data transformation process. Turban advocate data preparation model with data consolidation, data cleaning, data transformation and data reduction phases (Turban & Sharda & Delen, 2011, p. 209).
Berry and Linoff defined comprehensive data mining building model as an iterative process with several steps (Berry & Linoff, 2000, p. 48). The adopted model was used to establish the student data mining model for International School for Social and Business Studies from Slovenia:

- Data requirements identification: higher education teacher require to predict the students success in a specific course.
- Data acquizition:
    - course: Informatics on Bechelor Study Programmes – Economy in Contemporary Society,
    - academic years – number of students: 2010/11 (42 students), 2011/12 (32 students) and 2012/13 (32 students) – total 106 students,
    - the data was imported from web application Novis – Higher Education Information System – Teacher Module,
    - imported to MS Excel Table Tools,
    - with Data Mining add-in and MS SQL Server, installed on laptop computer.
- Validate, Explore, Clean and Transpose Data:
    - delete irrelevant columns (e.g. group, remark, individual activities points, registration number),
    - translation – from Slovene to English (columns title and content),
    - adjusting column order (logical order for success prediction, the last culmn is predictable »Final grade«,
    - status transformation: from several status type to yes/no value.
    - Employment transformation: from several status to yes/no value.
    - student name transformation to number.
- Add Derived Variables:
    - aditional column – »Study year«
    - aditional culumn derived form student name: »Gender«.
    - merge full time and part time students with additional column »Type of study«.
- Create Model Data Sets:
        - Student data sets columns (Table 1):
            - Study year (2010/11, 2011/12, 2012/13)
            - Student (order number 1 – 106)
            - Gender (female, male)
            - Student year of birth (e.g. 1988)
            - Employment (no, yes)
            - Status, e.g. sport etc. (no, yes)
            - Registration (first, repeat)
            - Type of study (full time, part time)
            - Exam condition (no, yes)
            - Activities points (0 – 50)
            - Exam points (0 – 50)
            - Final points (0 – 50)
            - **Final grade** (1 – 10) – prediction column.
    - Informatics 2010-11 and 2011-12 training data 2012-13 predict final grade.xls:
        - 106 students – row,
        - for 2010/11 and 2011/12 – 74 row of training data,
        - for 2012/13 – 32 row without predictable »Final grade« data
    - Informatics 2012-13 actual data.xls – 32 row of actual »Final grade« data
    - The data set form small number of examples but their content was estimated to be relevant for machine learning (Han & Kamber, & Pei, 2012, p.24).
- Choose Data Mining Technology:
    - MS offer three possibilities of data mining level:
        - Basic: using MS Excel Table tools Analyze Data Mining features;

- Intermediate: using MS Excel Data Mining Adds- in features,
- Expert: using MS SQL Server Data Mining capabilities.
- All levels od data mining are using algorithms from MS SQL Server Data mining, with different user interface, different technique and number of parameters, used to manage data mining process.
- For research purpose – Higher education teachers, we choose the basic level.
- Choose Data Mining modeling Technique:
  - MS Table tools offer several Data Mining Technique: Analyze Key influencers, Detect Categories, Fill from Examples, Forecast, Highlight Exceptions, Scenario Analysis, Prediction Calculation and Shoping Basket Analysis,
  - Some analysis are not suitable for given student data sets, e.g. Forecat, Scenario Analysis and Shoping Basket due to data or content limitation.
  - Among other technique, the most usable technique are Key Influencer and Fill from Examples, which we used for the following research.
- Train Model:
  - Using Fill from example technique, we run analysis several time, choosing »Final grade« as prediction culumn (e.g. Selecting column containing the examples),
  - Choosing different combination of columns: we found out the most relevant results by omitting student number (not relevant at all) and Exam points columns (directly define the final grade....).
- Choose Best Model – evaluate the results:
  - Comparing the results of prediction for 2012/13 student »Final grade« with the actual Final grade of the same student we can choose the best parameters for Fill from example data mining technique.
  - The final Data mining Fill from example predictive model in now ready for future student »Final grade« prediction, based on already known instances. The model can be used by confidence, until the following assumption is true (Berry & Linoff, 2000, pp. 61 - 63):
    - The past is good predictor of the future (if the student generation are changed their attitude and behavior may vary from the past and create different student patern.
    - The data is available – we assume the data will be always available for teachers.
    - The data contains what we want to predict – the data mining model, we built contains the relevant data.

Table 1: Students data sets

Study year	**Student**	**Gender**	**Year of birth**	**Employment**	**Status (sport...)**	**Registration**	**Type of study**	**Exam Condition**	**Activities points (50)**	**Exam points (50)**	**Final Points (100)**	**Final grade (10)**
2010-11	1	female	1988	no	no	first	full time	yes	46	46	92	10
2010-11	2	male	1990	no	no	first	full time	yes	38	33	71	7
2010-11	3	female	1990	no	no	first	full time	yes	39	30	69	7
2010-11	4	female	1990	no	no	first	full time	yes	47	35	82	8
2010-11	5	female	1989	no	no	first	full time	yes	39	36	75	7
2010-11	6	male	1990	no	no	first	full time	yes	38	30	68	7
2010-11	7	female	1990	no	no	first	full time	yes	39	36	75	7
2010-11	8	female	1990	no	yes	first	full time	yes	39	33	72	7
2010-11	9	male	1990	no	no	first	full time	yes	39	38	77	8
2012-13	106	female	1990	no	no	first	part time	yes	44	30	74	

2.2 Building student data mining model with Weka

The Data was also built using the WEKA Data Mining tool, were the following steps were conducted:

- Create Model Data Sets:

- The data was saved as described above, except from the last column ("The predited class") - The Final Grade. This attribute was transformed into an ordinal attribue using the following index: for values between 8-10 the "High" value was assigned, For Values between 6-7 the value "Medium" was assigned and for lower values than 6 the "Low" value was assigned. (In the case of decision tree M5P the class attribute remained the same as numerical).

- Choose Data Mining Technology:
  - The Weka tool was chosen.
- Choose Data Mining modeling Technique:
  - 3 Decision Trees techniques: J48, M5P and RepTree were selected. (In the case of M5P no conversaion of values for the class attribute was neccesary and the Final grade values were remained as numbers.
- Choose Best Model – evaluate the results:
  - Prediction rate accuracy for each trained model were evaluated in comparison with the related test set and the actual data respectivly.

3. STUDENT DATA MINING RESULTS

3.1 Key influencer for student “Final grade”:

At the beginning of the study, we wanted to find out which data (variables) are most powerful influencer for final grade prediction. Key Influencer Analysis is the right and useful tool for the job. Table 2 exhibitds the most powerful relative impact for different variables. For example, the last study year (2012-13), where “Final grade” is empty (we want to predict it) show “100” relative impact to favour empty column. Similar, high final points strongly favour high “Final grade”, and low “Activity points” or “Exam points” favour low “Final grade”. The results suggested to eliminate some of this columns from final prediction or at least try several combination of columns to produce relevant results.

Table 2: Key influencer Report for Final grade

Key Influencers Report for 'Final grade _10_'

Key Influencers and their impact over the values of 'Final grade _10_'

Filter by 'Column' or 'Favors' to see how various columns influence 'Final grade _10_'

Column	Value	Favors	Relative Impact
Study year	2012-13	<Empty>	100
Final Points _100_	92	10	100
Activities points _50_	39 - 42	7	100
Final Points _100_	77	8	100
Final Points _100_	85	9	100
Exam points _50_	9	2	100
Final Points _100_	53	2	100
Exam points _50_	13	2	100
Final Points _100_	51	2	100
Exam points _50_	8	4	100
Final Points _100_	41	4	100
Exam points _50_	21	4	100
Final Points _100_	66	6	100

3.2 Fill From Example – Student “Final grade” prediction for 2012/13:

The next step of study try to predict Student “Final grade” for missing 2012/13 by using Fill from example data mining technique, based on machine learning using previous examples from 2010/11 and 2011/12. For more relevant result “Student”, “Exam points” and “Final points” were eliminated from analysis. The Pattern Report in Table 3 shows diversity of influences. The results justified our decision to eliminate powerful key influencer from analysis.

Table 3: Fill from example Analyse for Student “Final grade”

Pattern Report for 'Final grade _10_'

Key Influencers and their impact over the values of 'Final grade _10_'

Filter by 'Column' or 'Favors' to see how various columns influence 'Final grade _10_'

Column	Value	Favors	Relative Impact
Type of study	part time	10	13
Activities points _50_	43,539 - 47,000	10	13
Registration	repeat	2	100
Study year	2010-11	2	13
Type of study	part time	4	17
Gender	male	6	33
Study year	2011-12	6	21
Activities points _50_	33,000 - 38,902	7	43
Status _sport____	yes	7	36
Employment	yes	7	31
Activities points _50_	38,902 - 41,221	7	18
Year of birth	1.967,148 - 1.982,240	8	25
Activities points _50_	43,539 - 47,000	8	21
Activities points _50_	43,539 - 47,000	9	36
Type of study	part time	9	24
Employment	no	9	10
Activities points _50_	41,221 - 43,539	9	10

Prediction for student “Final grade” for 2012/13 was the final part of data mining analysis, using Fill From Example Data Mining technique. The results are shown in table 4. The prediction based on data - knowledge, hidden in the student data. Algorithms use the data from year 2010/11 and 2011/12 for data mining prediction model (training data) and try to predict the missing student “final grade” data for 2012/13. As noticed all the student’s ”Final grade” are positive (above 6) because the majority of previous results are positive too.

Table 4: “Final grade” prediction for 2012/13

Study year	Student	Gender	Year of birth	Employment	Status (sport...)	Registration	Type of study	Exam Condition	Activities points (50)	Exam points (50)	Final Points (100)	Final grade (10)	Final grade _10__Extended
2012-13	75	female	1990	no	no	first	full time	yes	38	22	60		7
2012-13	76	male	1990	no	no	first	full time	yes	38				7
2012-13	77	male	1992	no	no	first	full time	yes	44				8
2012-13	78	male	1992	no	no	first	full time	yes	38	30	68		7
2012-13	79	male	1990	no	no	first	full time	yes	43	30	73		8
2012-13	80	male	1983	no	no	first	full time	yes	43	19	62		8
2012-13	81	female	1991	no	no	first	full time	yes	43	49	92		7
2012-13	82	female	1973	yes	no	first	full time	yes	44	42	86		8
2012-13	83	female	1989	no	no	first	full time	yes	42				7
2012-13	84	female	1989	no	no	first	full time	yes	38				7

2012-13	85	female	1990	no	no	first	full time	yes	38				7
2012-13	86	female	1976	yes	no	first	full time	yes	44	36	80		8
2012-13	87	female	1987	no	no	first	full time	yes	44	32	76		8
2012-13	88	male	1992	no	no	first	full time	yes	38	39	77		7
2012-13	89	female	1992	no	no	first	full time	yes	43	24	67		7
2012-13	90	female	1992	no	no	first	full time	yes	44				9
2012-13	91	male	1992	no	no	first	full time	yes	38	30	68		7
2012-13	92	male	1992	no	no	first	full time	yes	38	6	44		7
2012-13	93	male	1992	no	no	first	full time	yes	38	24	62		7
2012-13	94	female	1992	no	no	first	full time	yes	38				7
2012-13	95	male	1991	no	no	first	full time	yes	43	36	79		8
2012-13	96	male	1987	no	no	first	full time	yes	38	32	70		7
2012-13	97	female	1990	no	no	repeat	full time	yes	41				7
2012-13	98	female	1991	no	no	first	full time	yes	38				7
2012-13	99	female	1968	yes	no	first	full time	yes	44	38	82		8
2012-13	100	female	1986	no	no	first	full time	yes	44	46	90		8
2012-13	101	male	1989	no	no	first	full time	yes	38	17	55		7
2012-13	102	male	1990	no	no	first	part time	no					7
2012-13	103	female	1988	no	no	first	part time	yes	38	25	63		7
2012-13	104	female	1969	no	no	first	part time	yes	44				8
2012-13	105	female	1988	no	no	first	part time	yes	44				9
2012-13	106	female	1990	no	no	first	part time	yes	44	30	74		9

3.3 Interpretation:

- Interpretation is final but vital phase of data mining (Negnevitsky, 2011, p. 367). To evaluate the relevance of data mining student “Final grade” prediction the study compared the actual student’s “Final grade” with predicted one, shown in table 5. The following conclusions can be calculated and discussed:
- 32 students total, 20 students with actual Final grade (Exam),
- data mining predict all 32 students “Final grade”, included 12 (37,5%) without actual “Final grade”,
- with zero “Final grade” tolerance, the prediction was successful for 7 “Final grade” (21,8%),
- with +- 1 “Final grade” tolerance the prediction was successful for 11 “Final grade” (43,3%),
- the positive “Final grade” prediction was successful for 13 of 32 students (40,6%),
- but if 12 students (without actual “Final grade”) are omitted, the positive “Final grade” prediction was successful for 13 of 20 students (65%).

Table 5: Actual and prediction “Final grade” comparison

Study year	Student	Final grade (10)	Prediction
2012-13	75	4	7
2012-13	76		7
2012-13	77		8
2012-13	78	7	7
2012-13	79	7	8
2012-13	80	3	8
2012-13	81	10	7
2012-13	82	9	8
2012-13	83		7
2012-13	84		7
2012-13	85		7
2012-13	86	8	8
2012-13	87	8	8
2012-13	88	8	7
2012-13	89	4	7

2012-13	90		9
2012-13	91	7	7
2012-13	92	1	7
2012-13	93	4	7
2012-13	94		7
2012-13	95	8	8
2012-13	96	7	7
2012-13	97		7
2012-13	98		7
2012-13	99	8	8
2012-13	100	9	8
2012-13	101	3	7
2012-13	102		7
2012-13	103	4	7
2012-13	104		8
2012-13	105		9
2012-13	106	7	9

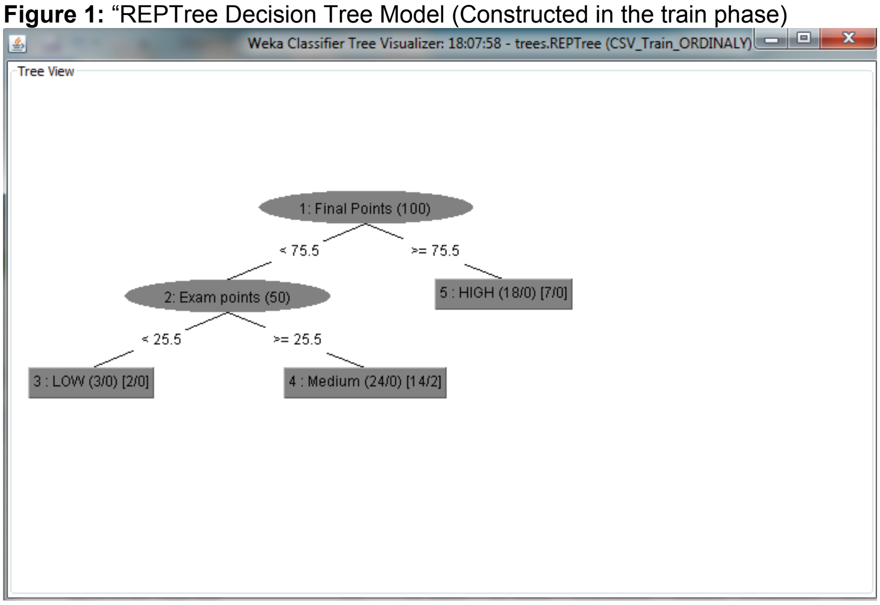
The study's results are not very clear. Final interpretation, that the positive "Final grade" prediction was successful for 13 of 20 students (65%) indicate the potential of data mining technique even for small student data sets. If larger data set or even more relevant student data were available the result relevance would improve, particularly when carefully combining parameters and columns in data mining analysis.

3.4 Key influencer for student "Final grade attribute" using the Weka Tool:

REPTree model:

Training Phase:
- Correctly Classified Instances: 97.0588%, (66);
- Incorrectly Classified Instances: 2.9412% , (2).

Figure 1: "REPTree Decision Tree Model (Constructed in the train phase)



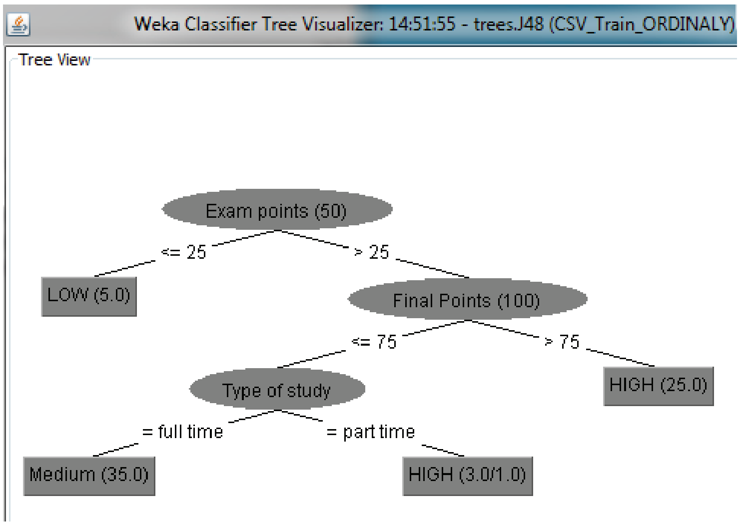
Testing Phase:
- Correctly Classified Instances: 100%, (20/20)

J48 model:

Training Phase:

- Correctly Classified Instances: 98.5294%, (67);
- Incorrectly Classified Instances: 1.4706%, (1).

Figure 2: J48 Decision Tree Model (Constructed in the train phase)



Testing Phase:
- Correctly Classified Instances: 90%, (18/20).

M5P model:
- Correlation coefficient: 0.9358
- Relative absolute error: 32.2884%

Figure 3: "M5P Decision Tree Model (Constructed in the train phase)

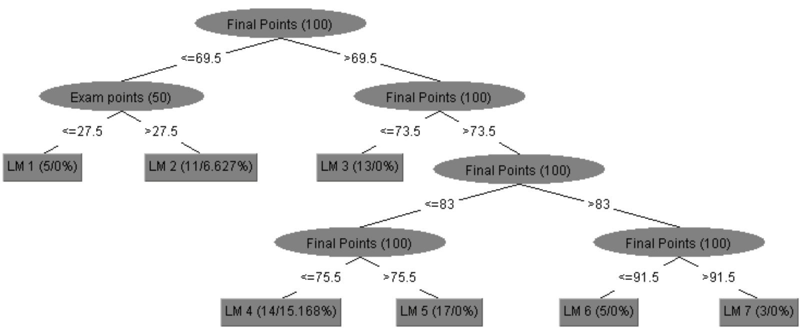


Table 6: "Final grade" prediction for 2012/13 Using 2 Decision Tree Methods analysis with Weka.

Study year	**Student**	**Final grade (10)**	**Prediction-J48**	**Prediction REPTree**
2012-13	75	4 (low)	low	low
2012-13	76			
2012-13	77			
2012-13	78	7 (medium)	medium	medium
2012-13	79	7 (medium)	medium	medium
2012-13	80	3 (low)	low	low
2012-13	81	10 (high)	high	high
2012-13	82	9 (high)	high	high

2012-13	83			
2012-13	84			
2012-13	85			
2012-13	86	8 (high)	high	high
2012-13	87	8 (high)	high	high
2012-13	88	8 (high)	high	high
2012-13	89	4 (low)	low	low
2012-13	90			
2012-13	91	7 (medium)	medium	medium
2012-13	92	1 (low)	low	low
2012-13	93	4 (low)	low	low
2012-13	94			
2012-13	95	8 (high)	low	high
2012-13	96	7 (medium)	medium	medium
2012-13	97			
2012-13	98			
2012-13	99	8 (high)	high	high
2012-13	100	9 (high)	high	high
2012-13	101	3 (low)	low	low
2012-13	102			
2012-13	103	4 (low)	low	low
2012-13	104			
2012-13	105			
2012-13	106	7 (medium)	high	medium

4. CONCLUSIONS

The study explores the possibility to predict the success rate of students enrolled in a course using contemporary data mining tools normally available to higher education teachers. The research clearly proves that the available desktop data mining tools have matured in terms of their usability and ease of use, and provide usable results without extensive investment.

The results of the study show that student data, available to higher education teachers via export/import features, carries enough student-specific characteristics in the sense of hidden knowledge which can be successfully associated with student success rates.

Despite the well-known fact that data mining algorithms work best on large data sets, the study focused on student data available to higher education teachers which is extremely limited and clearly falls into the category of a small data set. The results show that small student data sets in the specific data mining analysis did not limit the use of data mining tools.

Moreover were the weka tool, that was used as comparative analysis to MS Excel, showed that by using decision tree models a high prediction accuracy (especially with the REPTree model) is obtained (the accuracy was verified during the test phase). M5P regression tree didn't perform as well as the other decision trees since it requires more assumptions the formers. In fact, The REPTree is a fast decision tree learner which builds a decision/regression tree using information gain as the splitting criterion, and prunes it using reduced error pruning. The model only sorts values for numeric attributes once. Missing values are dealt with using C4.5's method of using fractional instances. Therefore, it may be deduced that since the predicted attribute was transformed into an ordinary value, REPTree was less sensitive to missing values than J48 thus prediction accuracy on test set was better performed. However on Train set it obtained a slightly less performance than J48 (~97% v.s. ~98%). J48 is a slightly modified C4.5 algorithm that generates a classification-decision tree for the given data-set by recursive partitioning of data. The decision is grown using Depth-first strategy. The algorithm considers all the possible tests that can split the data set and selects a test that gives the best information gain. Concerning the evaluated data J48 was less accurate than REPTree, which can be postulated since it is a more sensitive algorithm than REPTree.

In general, the study answers the research questions and supports the promising conclusions that data mining for small data sets has a real potential to become a serious part of higher education teachers' knowledge management systems. According to Nonaka's process model of a knowledge-based firm (Nonaka & Toyama & Hirata, 2008, p. 27), it is very important that organisations explore tacit knowledge, not only in their employees' heads. Sometimes it is more important to explore the knowledge hidden in an organisation's data and transform it into explicit knowledge to improve the organisation, in our study the quality of the educational process.

The authors hope that these conclusions will encourage teachers to incorporate data mining tools into their daily work.

REFERENCE LIST

1. Andonie, R. (2010). Extreme Data Mining: Inference from Small Datasets. *Int. J. Of Comppputers, Communications & Control, 5*(3).
2. Becerra-Fernandez, I., & Gonzales, A., & Sabherwal, R. (2004). Knowledge Management, Challenges, Solutions, and Technologies. *Pearson Prentice Hall*.
3. Berry, M., & Linoff, G. (2000). Mastering Data Mining. The Art and Science of Customer Relationship Management. *Wiley.*
4. Bukowitz, W., R., & Williams, R., L. (2000). The Knowledge Management Fieldbook. *Prentice Hall.*
5. Gomezelj Omerzel, D. & Biloslavo, R. & Trnavčević, A. (2010). Management znanja v visokošolskih zavodih. *Univerza na Primorskem, Fakulteta za management Koper.*
6. Han, J., & Kamber, M., & Pei, J. (2012). Data Mining, Concepts and Techniques. *Morgan Kaufmann*. Jashapara, A. (2011). Knowledge Management, An Integrated Approach. *Prentice Hall. 2. Ed.*
7. Negnevitsky, M. (2011). Artificial Inteligence, A Guide to Intelligent Systems. *Pearson Education Limited. 3. Ed.*
8. Nonaka, I., & Toyama, R., & Hirata, T. (2008). Managing Flow, A Process Theory of Knowledge-Based Firm. *Palgrave Macmillan.*
9. Osei-Bryson, K.-M. (2010). Towards supporting expert evaluation of clustering results using a data mining process model. Information Sciences, *180*(3), 414-431.
10. Sinha, A. P., & Zhao, H. (2008). Incorporating domain knowledge into data mining classifiers: An application in indirect lending. Decision Support System, *46*(1), 287-299.
11. Tso, G. K. F., & Yau, K. K. W. (2007). Predicting electricity energy consumption: A comparison of regression analysis, decision tree and neural networks. Energy, 32,1761-1768.
12. Turban, E., & Sharda, R. & Delen, D. (2011). Decision Support and Business Intelligent Systems. *Pearson. 9.ed.*
13. Wang, H., & Wang, S. (2008). A knowledge management approach to data mining process for business intelligence. Industrial Management & Data Systems, *108*(5).
14. Yuan, J. L., & Fine, T. (1998). Neural-network design for small training sets of high dimension. IEEE Transactions on Neural Networks, *9*.
15. Wan, S., & Lei, T.C. (2009). A knowledge-based decision support system to analyze the debris-flow problems at Chen-Yu-Lan River, Taiwan. Knowledge-Based System, *22*(8),580-588.
16. Zanakis, S. H., Fernandez, I.B. (2005). Competitiveness of nations: A knowledge discovery examination. European Journal of Operational Research, *166*(1), 185-211.
17. Zhuang, Z. Y., Churilov, L., Burstein, F., & Sikaris, K. (2009). Combining data mining and case-based reasoning for intelligent decision support for pathology ordering by general practitioners. European *Journal of Operational Research, 195,* 662-675.