Success Prediction System for Student Counseling using Data Mining

Jörg Frochte and Irina Bernst
Dept. of Electrical Engineering and Computer Science,
Bochum University of Applied Sciences, 42579 Heiligenhaus, Germany

Keywords: Data Mining, Classification, Supervised Learning, Information Privacy, Tertiary Education.

Abstract: A framework how to use data mining of central exam data for the prediction of student success in bachelor degree courses is presented. For the prediction a supervised learning approach is used based on successful and unsuccessful student biographies. We develop a traffic light rating system and present results for two different kinds of bachelor degree courses; one in economics and one in engineering. We discuss applications for students and student counseling institutions as well as the limitations dealing with information privacy aspects, especially under the conditions regarding data mining in Germany.

1 INTRODUCTION

The application field of knowledge discovery from data bases is wide. One of these interesting fields arises in the education system.

1.1 Research Questions and Contributions

In this paper we apply techniques from knowledge discovery from data bases to build a prediction system, which can be helpful in the context of student counseling. With this we mean institutions or persons in the tertiary education that offer counseling to help students work through their difficulties and find ways of managing their study and life situation.

The first contribution of our work relates to the construction of a framework for a success prediction system on the degree course level. We discuss the question of the relevant feature space including practical issues. This system is based on some static parameters concerning the qualifications of the student, but mainly on the dynamic behavior during his study. It uses data bases that naturally occur during the student's time at a university. The most important data source we are considering is the data base of the exam office, in which the data accumulates after every examination period. In the case a student signs on a regular course exam, additional data is being collected whether he or she passes, fails or withdraws. In the case the student chooses to not sign on a course this is recorded as well. So our approach doesn't need any additional data collection like e.g. surveys at all.

Other contributions of our research relate to the development of a traffic light rating system based on the approach above. This provides a practical case study for our approach.

1.2 Related Work

In the context of knowledge discovery from educational data bases the term Educational Data Mining is nowadays used more and more. The work (Romero and Ventura, 2007) provides a good survey on this topic in the early years from 1995 to 2005. Often this covers approaches contributing to theories of learning or the learning sciences or as well the prediction of the student's future learning behavior. As in (Baker and Yacef, 2009) this has often a kind of low level context. This means in most cases the Educational Data Mining community tends to consider student modeling on the level of courses or single learning activities.

In this work – with a whole degree course as level for the prediction – we consider a higher level of abstraction concerning learning activities. A quite closely related work is (Osmanbegović and Suljić, 2012), in which different learning techniques were compared concerning the success in the course *Business Informatics*. The work was based on 257 data records and achieved a prediction accuracy between 71.2% and 76.65% depending on the used technique.

More to the initial conditions focuses the work (Kovačić, 2010). It mainly uses socio-demographic features like age, gender, ethnicity, education, work

Frochte, J. and Bernst, I.
Success Prediction System for Student Counseling using Data Mining.
DOI: 10.5220/0006036401810188
In *Proceedings of the 8th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management (IC3K 2016) - Volume 1: KDIR*, pages 181-188
ISBN: 978-989-758-203-5

status, and disability. Beyond this, aspects like the fact, whether a bachelor of business or bachelor of applied science is aimed, are used. Therefore, the prediction here is mainly independent of the students' behavior during their study. The CART approach used in (Kovačić, 2010) was based on 453 data records and reaches an overall percentage of correct classification of 60.5%. In (Jishan et al., 2015) the goal is a prediction model for the final grade. The used data set contains 181 instances from a course titled *Numerical Analysis* at North South University, Dhaka, Bangladesh. The highest accuracy of about 75% was reached using Artificial Networks and Naive Bayes classification.

2 KNOWLEDGE DISCOVERY IN EXAM DATA BASES AND USE CASES

We use Knowledge Discovery in Data Bases according to (Fayyad et al., 1996) and apply this concept to the demands of exam data bases especially in Germany or states with similar restrictions concerning data protection and informational self-determination. Germany has quite strict laws concerning which, where and by whom data is processed. For example, aspects like the social background or migration background is not covered for data collection and processing by (Law of the FRG, 2016). Therefore, the suggested framework tries to be most careful concerning this issue and shows, how it is still possible to provide a tool for student counseling based on exam data records with these limitations.

2.1 Suggested Framework

Because of the discussed limitations we developed the following processing work flow. As figure 1 illustrates, the starting point is the data base of the examination office of a university. It contains all data about a student that a university has. To keep the data maximum secure in a first step, the data of relevant features is anonymized and copied to a new data base. This is a full automatic process that can be performed on the computer system of the examination office in a regular schedule. Therefore, the risk of stolen data or illegal use is the same as before. At this point the suggested process does not contain any new party or environment. The features are discussed more detailed in section 2.2 as well as the necessary preprocessing of the data. The last preprocession step yields a training set from which a prediction system is built. The resulting system, e.g. a multilayer perceptron (MLP), is trained. The important aspect is that most software systems based on machine learning algorithms – after they have been trained – can act independently of the used training data base. For example, in artificial neural networks like multilayer perceptron knowledge is compressed in the weights w_{ij} of each layer, which means a few matrices of double values. Concerning data security it is impossible to reconstruct a single record of the training data base from these matrices. Therefore, a trained system can be distributed without interfering with data protection issues among e.g. other institutions of a university.

While after the completed training the software unit itself does not contain personal data of the students from the training set, it of course still needs the input data vector of the student it should predict the study success for. Thus, for this software system there are at least two applications.

1. Use as **personal advisor or alarm system** for the students themselves. If a student signs in for the alarm system every exam period, his behavior can be rated and he may receive a feedback in terms of a traffic light rating system. Red would mean that he or she should consider seeking for help, e.g. at a student counseling office. Green means everything is fine, and yellow is obviously in between. For the student that might mean to watch carefully his own steps and to consider what was different compared to the last *green semester*. If the last exam period was red, yellow could mean, that someone is on the right way and things are getting better.

2. Use as **tool** for the **counseling offices**. In the same way as a single student can use it for himself it can also act as *second opinion* for professional counselors. This is always possible, because a counselor can access the student's data during counseling.

If the current law allows it, of course it would be possible to e.g. process the data of all students a counselor is responsible for and to seek for candidates, who might need additional support. In countries, in which this is not automatically possible by law, there is in general the option to ask students for a permission, when they sign in for the university. Because this will be non-obligatory, only a subset of students will be covered by this usage scenario.

2.2 Practical and Data Quality Issues

After the introduction of the bachelor and master degree programs in association with the Bologna Process the universities in Germany have built up a wide range of different degree courses. All of them use the European Credit Transfer and Accumulation Sys-

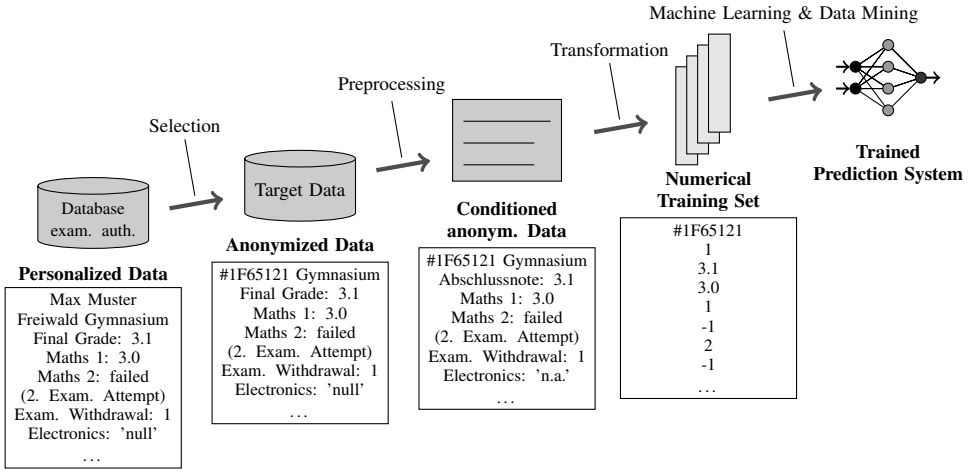

Figure 1: Knowledge Discovery in Exam Data Bases according to (Fayyad et al., 1996).

tem (ECTS). One semester corresponds to 30 ECTS credits. Today there are about 18,000 degree courses. Some of them only differ in details, some differ totally. Nevertheless, most of them are descendants of traditional diploma degree courses. In engineering for example there are about five types: civil engineering, electrical engineering, mechanical engineering, mechatronics and depending on the definition computer science.

So one might expect the level of supersets of degree courses to be a reasonable level for learning approaches. Considering this in detail it yields that this level is not very promising for our approach. The reason is that for the presented prediction system the differences between the degree courses are hard to be modeled. For example, let us suppose several universities provide a degree course for electrical engineering. These degree courses all contain foundation courses, e.g. in mathematics, physics. But all of the degree courses will have different exam regulations. Most of them might limit the number of trials to three, some not. Some will provide grades for the courses, some just attributes like *passed* or *failed*. Some even might have rules like you need *m* of *n* foundation courses etc. All of these aspects might change the behavior of the students in the system and therefore effects the learning methods. Beyond this, a degree course is in these terms a moving target. Every 5th up to 7th year the universities have to evaluate their degree courses and in general change some aspects.

Therefore, it is reasonable to look for features that are independent of the particular degree course. From a scientific point of view we suggested – in addition to the exam data records – also to analyze the impact of personal data features, like *gender/sex* and *year of birth*. Also other studies analyzed personal features, like (Jirjahn, 2007) that indicates a strong correlation between success and the age when a person starts to study as well as the grade of the qualification for university entrance. The age is again an important factor in (Mosler and Savine, 2004). Beyond this, the published results indicate that the gender is not a relevant feature for the tertiary education level. Other social economic features might be very important for the success in the German university system as (Erdel, 2010) indicates. Beside existing data bases Erdel used a survey, which in opposite to (Mosler and Savine, 2004) indicates that both, age and gender, are very important. In general, considering the OECD studies, e.g. (OECD, 2010) p. 43 – 45 and 95, one could expect that at least in Germany more social economic features have a significant impact.

Nevertheless, because of legal concerns it has not been possible to include these social economic features in our data base. Therefore, we were restricted especially concerning sex/gender aspects. The age is not directly included, but we were allowed to use both data records, *the year of the qualification for university entrance* and *the starting year of degree course*, which together correlate with the age. Therefore *age* is weakly included.

We concentrate our study on two very different degree courses: A bachelor degree in economics and one in engineering. They differ much concerning their structure and size of the data records.

After eliminating incomplete or obviously corrupt data, the sample comprised 952 students of economics and 261 of engineering. All of theses samples are completed degree course biographies labeled for this particular degree course with *success* or *dropout*. *Dropout* means that the student left the degree course at this particular university. Right now it is not pos-

sible to track the students after they left a single university. So some of them might leave e.g. because of personal reasons following their cohabitation partner to another town and continue their studies there. In the new university these biographies again cause data sets, which may lead to issues as shown in section 4.3.

2.3 Feature Selection

We prepared our training set, which contains 952 students of economics and 261 of engineering, with the following features, partitioned into two categories. The first are the static features, which will be constant during the whole degree course biography:

1. Grade of the qualification for university entrance
2. Year of the qualification for university entrance
3. Kind of entrance qualification
4. Starting year of degree course

The best categories are the dynamic features, which means that these values will change after every examination period based on the behavior of the student:

5. Success coefficient = $\frac{\text{Number of successful exams}}{\text{Number of possible exams}}$
6. Mean grade of all successful exams
7. Number of exam trials
8. Number of withdrawals
9. Sum of reached ECTS

As we will see in section 4.1 these features are highly diagnostic compared to the static features above.

With these features one has the possibility to model very different types of students. For example, we do not have the information, whether a student considers himself as part-time student. Germany has no tuition fees, so this is quite common. But a successful part-time student can be modeled with our feature set as well. This group could be classified by a low number of withdrawals and a good mean grade in contradiction to an average success coefficient, which directly correlates with the number of exam trials and a low sum of reached ECTS compared to the semester. Therefore, we could also classify unsuccessful and successful part-time students.

To select the features one must keep in mind that in general e.g. the significance tests for a single feature might differ from one degree course to another. To illustrate this let us consider the *grade of the qualification for university entrance*.

The results in table 1 and table 2 make us – independent of the used method – conclude that with a significance level of 5% we can reject the null hypothesis

Table 1: Significance Test (Pearson).

	Pearson's linear correlation coefficient	***p*-Value**
Economic	-0.0875	0.0074
Engineering	-0.2393	0.0001

Table 2: Significance Test (Spearman).

	Spearman's rank correlation coefficient	***p*-Value**
Economic	-0.0734	0.0246
Engineering	-0.2399	0.0001

for both degree courses. Therefore, there is a correlation between the *grade of the qualification for university entrance* and the chance to successfully graduate in the degree course. The correlation for the economic degree course is much weaker than for the engineering course. The suggested explanatory model is that the engineering degree course has stronger dependencies to teaching contents at school, e.g. physics or mathematics.

Features like *kind of entrance qualification* are on the other hand more important for degree courses at a university of applied sciences than at traditional universities. At a traditional university this feature is nearly always the identical constant value for all students. This assumption does not hold for universities of applied sciences, where the students have a broader spread of entrance qualifications.

Nevertheless, in all cases we analyzed that the success coefficient (feature no. 5) is the most important feature and this is very robust over all degree courses.

3 SUPERVISED LEARNING AND TRAFFIC LIGHT RATING SYSTEM

In this section we describe the approach of using the supervised learning for developing a predictive system of the students' success and based on this the traffic light rating system.

3.1 Supervised Learning Approach

For our approach we need a data set with students, who already have completed a bachelor degree course or have chosen to dropout. As a result, we have a data base with labeled training and testing data.

We present results for two different training methods. On the one hand a common multilayer perceptron (MLP) with one input layer, two hidden layers

and one output layer. All neurons used sigmoid functions and the weights have been trained using backward propagation. On the other hand we have got the discriminant function analysis as statistical method for behavior prediction or classification of objects. While the MLP is used as function approximation between the values 0 for dropout and 1 for alumnus using the features described above, the discriminant function analysis works a bit differently: Its goal is to analyze the group differences, meaning the investigation of the two groups of students with regard to the given features.

Both methods were used as follows to predict the success of the student in the particular bachelor degree course. As discussed in section 2.2 the degree courses are quite different. To avoid a new feature space for every degree course we trained a single system for every semester of every degree course. The training per semester includes peculiarities of the specific semester in the specific degree course into the achieved model of the learning system. So if e.g. the first two semesters are quite hard with a big drop rate and the following four ones are – for the remaining students – smoother, then this behavior is included in the models. This has a lot of advantages, e.g. it avoids explicitly modeling the examination regulations and other specific aspects of the degree course. Of course, this also has disadvantages mainly that for a new course program developed after the evaluation cycle discussed in section 2.2 it is still open, how to transfer the achieved knowledge to a derived degree course.

3.2 Traffic Light Rating System

In section 2.3 we proposed a model with nine features that primarily conduces to success concerning the classification of the students. The use of the methods from section 3.1 with these features leads to the approach for the traffic light rating system:

1. The trained system receives the nine features from section 2.3 for a particular student.
2. The dropout probability for the student is calculated according to section 3.1.
3. The traffic light rating system takes the dropout probability of the previous semester into account. The weighted linear extrapolation of dropout probabilities P_i of the semester i and P_{i-1} of the previous semester $i-1$ yields $\hat{P}_i = P_i + \alpha \cdot (P_i - P_{i-1})$ with the coefficient $\alpha \in [0,1]$. Thus, the system is based on calculation of the dropout probability trend. For the first semester we use $\hat{P}_1 = P_1$.
4. To illustrate the prediction in traffic lights, the range of $\hat{P}_i$ from 0 to 1 is divided into three areas: The first area (green) is from 0 to 0.35, the second area (yellow) from 0.35 to 0.65 and the third area (red) from 0.65 to 1.

4 RESULTS

We compared the different methods and approaches. The results are shown for the test set, which prevents over-fitting effects. As we will show below, it turns out that the total prediction accuracy is mainly defined by the selected features.

The results of the test sets may differ depending on the selected data records. For example, a test set based on 15% of the total data sets are just 39 data sets in engineering. To provide meaningful results the systems were trained multiple times with randomly selected sets, evaluated concerning the achieved accuracy, and afterwards all of the results were arithmetically averaged.

In the tables below the value of correctly classified alumnus means, how many of the persons, who according to the data base finished the degree course, were correctly classified as alumnus; the same for the ones, who dropout of the degree course independent of the specific reasons.

4.1 Results using Discriminant Function Analysis

We start with the results achieved on discriminant function analysis. In all tests, see e.g. table 3, it turned out that the discriminant function analysis as method on this problem set tends to be significantly more correct for the alumnus subset than for the dropout subset.

Table 3: Prediction after the first semester prediction.

Course	Correctly Classified		
	Total	Alum.	Dropout
Economics	76%	79%	68%
Engineering	82%	88%	80%

Let us assume for the application scenario that we have a degree course with 30% dropout rate and about 200 freshmen. The system would classify about 110 of the alumnus set correctly and send 30 to the counseling. On the other hand about 40 of the dropout set would be correctly classified and 20 would be misclassified. Under these conditions the system does not work entirely satisfactorily, because 70 persons would maybe be asked to seek for an appointment at the counseling office, while 57% will really need it.

For engineering with the higher rates it turns out better. Under the same conditions 122 alumni are classified correctly and 18 would be sent to the counseling by mistake. On the other hand 48 dropouts would be detected correctly. There we end up with about 73% of the 66 persons, who will be sent for counseling and really need a counseling appointment.

These are the rates and the prediction accuracy in the first semester. As table 4 below shows, this accuracy will rise, if one considers higher semesters.

Table 4: Prediction accuracy for different semesters.

Semester	Correctly Classified	
	Economics	Engineering
1	76%	83%
2	78%	85%
⋮	⋮	⋮
6	82%	89%

Nevertheless, for student counseling mainly the first two semesters are of major interest. If the system receives data for the second semester, the student will have studied about one year and have already set the course for another half year.

Another aspect that table 4 shows, is that both degree courses differ concerning the prediction quality, whereas both gain about 6% points from the first to the sixth semester.

The prediction quality between both degree courses differs between 6% and 7% points. The reason is not the size of the data base because the number of data records for economics is higher. One reason might be that students of the economic degree course might be more heterogeneous compared to the engineering students and therefore the missing social economic features might have a higher impact here.

Beyond this, for the economic degree course the static features provide no additional information – in opposite to some other degree courses. If one just uses the static features for the prediction, we receive the results shown in table 5. So in economics one can see

Table 5: Prediction after the first semester using feat. 1 – 4.

Course	Correctly Classified		
	Total	Alum.	Dropout
Economics	53%	47%	65%
Engineering	65%	64%	65%

that guessing is nearly as effective as using the prediction system. It turned out that these features have not enough information for this course. For the engineering course on the other hand the output is beyond the rates achieved in (Kovačić, 2010) for static features. So for this course they provide useful information.

4.2 Results for the First Semester using a Feedforward Neural Network

With the following results we would like to emphasize that the model for the prediction is quite simple and up to this level its success mainly depends on the data base and its quality.

To do this we used a multilayer perceptron (MLP) with two hidden layers of equal length as an alternative to the discriminant function analysis. As table 6 and 7 indicate, it is possible to model the main behavior with three neurons in both layers. Raising the number of neurons up to ten in each layer only leads to small changes. After that point the results for the studied six semesters of both bachelor degree courses won't improve anymore or will get even worse on the respective testing set.

Table 6: MLP for Economics (1. Semester).

Hiddenlayer		Correctly Classified		
1	2	Total	Alumnus	Dropout
3	3	75%	76%	73%
10	10	76%	77%	72%

Comparing table 6 and 3, both approaches reach about the same rate for correct classification on the total set. The only significant difference is about their behavior on the two subsets of successful alumnus and dropouts. The multilayer perceptron tends to be more correct for the dropouts and the discriminant function analysis for the alumnus.

Table 7: MLP for Engineering (1. Semester).

Hiddenlayer		Correctly Classified		
1	2	Total	Alumnus	Dropout
3	3	85%	79%	88%
10	10	85%	80%	87%

The same is true for the results in table 7. Beyond this, for this degree course the multilayer perceptron produces slightly better results compared to the discriminant function analysis.

4.3 Application on Traffic Light Rating System

Now we demonstrate the application of this prediction approach to the traffic light rating system described in section 3.2.

Figure 2 shows the estimated dropout probability (blue graph) and the suggested traffic light system with $\alpha = 0.5$. The two students are members of the test set and finish this degree course as alumni.

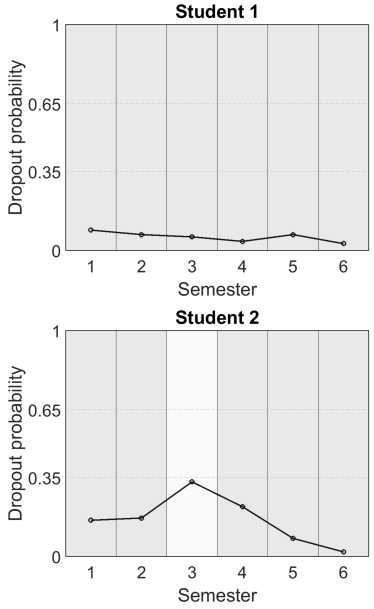

Figure 2: Traffic light rating for alumni in economics.

The traffic light rating considers the dropout probability for all semesters as low. The provided feedback was correct all of the time. Even the yellow sign for student 2 is reasonable, because of the changing of the dropout probability. In this case the student managed it on his / her own, but the yellow sign with a still quite low dropout probability would provide a good feedback.

In figure 3 we see different time lines, which are all marked as dropout in the data base. Student 4 dropped out after the third semester. After that point the dropout probability is 1. Student 3 is an example for unusual behavior that makes it hard to achieve higher certainty rates. After a bad start it became better and better, but ended with a dropout in a higher semester. The cause might be a shift to another university or personal reasons. In these cases a third group like *continues studies elsewhere* or similar could be helpful.

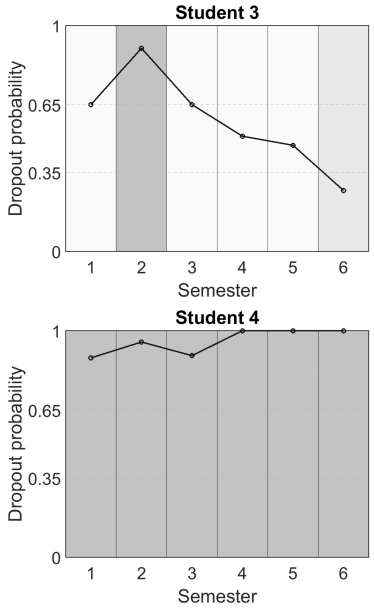

Figure 3: Traffic light rating for dropouts in economics.

The same experiments were performed for the engineering degree course. Two alumni students are shown in figure 4. The system works in general fine as shown e.g. for student 5. However, there are exceptional cases as shown with student 6. Here, the reason is that the student changed the degree course. In such a case the data has all the ECTS credits that have been transferred from the former degree course listed in one semester. Other features like the trials (often being set to 1) suffer as well. So this data set is very hard to predict by a learning system, because it is highly irregular.

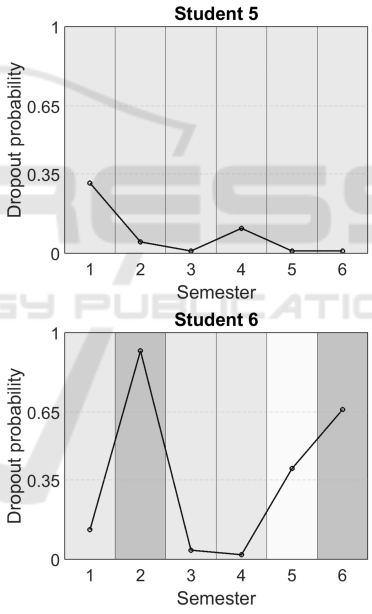

Figure 4: Traffic light rating for alumni in engineering.

4.4 Benchmark of the Results

In this section we will discuss, whether the achieved results meet already the considered use cases and how they can be seen in comparison to the results in the related work section. We considered two main application cases, the first one as tool for a personal advisor and the second one as tool for a counseling office.

The results for the engineering degree course are very promising. With the prediction accuracy of the MLP it should be possible to use the developed prediction system at least as a first filter for a counseling

office as to the question, which students might need further attention. Because the counselors as professionals will be able to bring the output of the algorithm into line with their experience, the rate will be good enough.

Probably most of the students would be able to balance the statistical rating of the system against their personal appraisal. Nevertheless, for some students a misclassification of the tool might encourage them with their wrong opinion or even unsettle persons with a low self confidence. Therefore, we consider the results as still not good enough for the application in the suggested use case as personal advisor but as a reasonable tool for counseling offices.

If we compare the results of the overall percentage of correct classification of 60.5% in (Kovačić, 2010), 76.65% (Osmanbegović and Suljić, 2012) and 75% in (Jishan et al., 2015) the reached classification rate for the bachelor degree course in economics with 75%-76% is in a good region. The rates of 85% using MLP and 82% with the discriminant function analysis for the degree course in engineering are very good.

5 CONCLUSION AND FUTURE PROSPECTS

In this paper, we proposed an approach for the success prediction of a whole bachelor degree course. The proposed key idea was to learn on a mixture of static features and dynamic features. With this we introduced a novel feature set and it is beyond this possible to model every bachelor degree course independent of the current subject area. The achieved results of this generic approach are at least in the common interval of related results or even better.

In addition, several avenues of future work have been identified which we expect to offer further improvements. To improve the percentage of correct classification we assume social economic features in contradiction with an improved tracking of dropout students. Another open question is, if it will be possible to transfer knowledge of old bachelor degree courses to a refined version after the evaluation phase. Beyond this, one has to keep in mind that the alumnus set is bigger than the dropout group in contradiction with the fact the all approaches are less accurate on this subset. This is an issue for the counseling office usage scenario because of the subset of alumnus classified as dropouts. These persons will unnecessarily tie up capacities. Therefore one future prospect is to develop a second stage in which just the persons classified as dropout are evaluated again.

Due to the promising results with further research concerning these aspects we expect that knowledge discovery in exam data bases will become a very important tool in student counseling and academic quality control.

ACKNOWLEDGEMENTS

We would like to thank C. Kaufmann, P. Bouillon & S. Rüsche for support and discussion. This work is supported by a grant from the MIWF NRW.

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