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OU Analyse: analysing at-risk students at The Open University

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By: Jakub Kuzilek, Martin Hlosta, Drahomira Herrmannova, Zdenek Zdrahal, Jonas Vaclavek and Annika Wolff

The OU Analyse project aims at providing early prediction of 'at-risk' students based on their demographic data and their interaction with Virtual Learning Environment. Four predictive models have been constructed from legacy data using machine learning methods. In Spring 2014 the approach was piloted and evaluated on two introductory university courses with about 1500 and 3000 students, respectively. Since October 2014 the predictions have been extended to include 10+ courses of different level. The OU Analyse dashboard has been implemented, for presenting predictions and providing a course overview and a view of individual students.

Contents

Executive Summary

This case study has been published as part of the practitioner track of the Learning Analytics and Knowledge conference LAK15, Scaling Up: Big Data to Big Impact, 16-20 March 2015[1].

The objective of the OU Analyse project is to predict 'at-risk' students as early as possible within a course presentation so that interventions are meaningful and cost effective. For that purpose two types of data are used: demographic (static) data and student interactions with the Virtual Learning Environment (VLE) system. Using Bayesian approach the most relevant VLE activity types (i.e. accessing important resource, student forum, etc.) are selected. Every week, together with demographic data, selected activity types are used to build four predictive models. These are:

- Bayesian classifier,

- Classification and regression tree (CART),

- k Nearest Neighbours (k-NN) with demographic/static data,

- k-NN with VLE data.

Models capture different properties of input data and provide complementary results. A list of students at risk of not submitting the next assessment is sent every week to the course chairs and the student support team, who are responsible for contacting and supporting the students.

For presenting the predictions and providing information about the state of the course the OU Analyse dashboard with two views has been implemented and is being deployed across selected courses at the Open University (OU).

In the spring semester 2014, weekly predictions were being sent to two introductory courses where student retention was an issue. The precision of the predictions increased from about 50% at the beginning of the semester to more than 90% at the end. Recall was stable at around 50% with a drop to about 30% at the very end, due to incomplete results of the preceding assessments.

In the past term (autumn 2014) the main goal was to scale up to support more courses. The inclusion of more courses of different level however brought new challenges, such as the lack of historical data, which could be used for building the predictive models. Some courses, particularly second and third year courses with higher retention, requested the prediction of an expected score in addition to an indication of potential success/failure. This information is used to motivate the students to improve their final result.

Introduction

Early detection of students at risk of failure allows the university to execute timely interventions, to help the students to stay on track. Analysis and summary results of courses can also be a valuable resource for the course teams to identify problematic milestones and make improvements for future course presentations. In addition, the analysis of student interactions with VLE and the prediction of their performance could be important instruments in supporting Massive Open Online Courses (MOOCs) such as Coursera or FutureLearn.

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[1] *http://lak15.solaresearch.org/home*

The OU is the biggest university in the United Kingdom, offering several hundred distance learning courses. These can be studied both as part of a university degree or as standalone modules. No previous education is required to enrol at the OU. Students use VLE for accessing study materials and for submitting their assignments. Typically, students participating in a course are divided into smaller study groups of no more than twenty students. Each group has an associate lecturer assigned to them. They grade the students' assignments and exams, provide general advice and guidance, etc. To support students who are at risk of failing, the OU also implements various interventions, such as phone calls from specialised student support teams. The number of students studying each course can reach several thousand and therefore, the interventions have to be carefully planned.

Previous and related work

Machine learning techniques for identifying students at risk of failing have been investigated and described in a number of publications (Arnold & Pistilli, 2012; Baradwai & Pal, 2011; Huang & Fang, 2013; Kabra & Bichkar, 2011; Pandey & Sharma, 2013; Romero, et al., 2013; Wladis, et al., 2014; Wolff, et al., 2014; Hlosta, et al., 2014).

The basic idea is to use legacy data to learn the predictive models and to use these models to make predictions on currently running courses. This information can be helpful for the course staff who are planning interventions or other strategies to improve the student retention rate. In (Huang & Fang, 2013), the models for identifying success or failure of students were trained on the data about their previous study results. It has been observed that failure predictions for the first year courses are important, because the failure rate is usually high but with additional support many students can be saved (Wolff, et al., 2014).

Behaviour of students in the VLE can be used to build predictive models for online courses. These could be just simple summary statistics such as those used in (Romero, et al., 2013). When neither the students' previous study results nor their VLE activities are available, demographic data can be utilised as the only available source of information (Wladis, et al., 2014).

Our work builds on the previous research at the OU (Wolff & Zdrahal, 2012; Wolff, et al., 2014; Wolff, et al., 2013; Wolff, et al., 2013; Hlosta, et al., 2014). The initial approach was utilising decision trees trained on the data describing student behaviour in the VLE complemented by the scores of the previous assessments (Wolff & Zdrahal, 2012; Wolff, et al., 2013). The more recent work, which enriched the input data with the demographic features, reported an improvement in the predictions on three analysed courses (Wolff, et al., 2013). The key finding in (Wolff, et al., 2014) was the importance of the early identification of students at risk, even prior to the first assessment in the course. The students who fail or do not submit the first assessment are very likely to withdraw or fail the whole course.

Problem specification

For identifying students at risk we use knowledge about students' behaviour and performance in the current presentation, their demographic data and data about the course and performance of students in previous presentations of the same course. In this task we do not consider students' previous or current performance in another course. This is shown in Figure 1. The assessment cut-off dates (A_N) split the course into several periods.
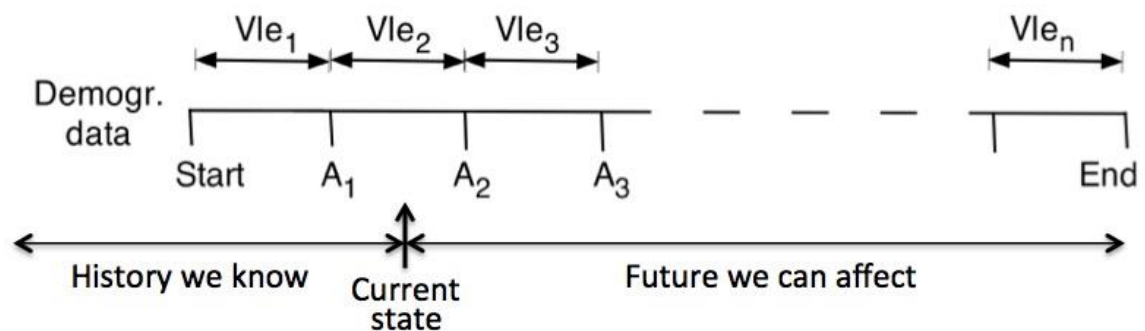
Figure 1: Course structure with assessments and VLE activities

Given demographic data, the results of assessments achieved so far and VLE behaviour, the goal is to identify as early as possible the students who are at risk of failing or not submitting the next assessment and for whom the intervention is meaningful. By meaningful intervention, we mean that the student can be helped to pass the module and the overall cost of interventions is affordable. Predictions about the future behaviour of the student are based on experience with students with similar characteristics in a previous run of the same course.

Data

Data collection

Student demographic data and the information about their interactions with the VLE are stored in the university data warehouse. Data are collected from the warehouse and transformed into the format required by the OU Analyse dashboard. Currently we are collecting data from eleven courses across two terms (autumn 2014 and spring 2015). The number of students participating in each course varies from several hundred to several thousand. For every student, typical demographic data are collected. These include age, previous education, gender, the number of credits the student is currently registered for and the number of times the student previously attempted the course. VLE data represent student's interaction with the on-line study material and contain information about number of clicks students made on specific educational resource. Each VLE material is labelled by an activity type, which indicates what kind of role it plays in the learning process. For example, "resource" activity type refers to a segment of text the student is supposed to read, "forum" points to the forum space of the course etc. VLE data are collected daily, however for the purpose of predictive modelling we use summarisations.

Importance of VLE data

Before the VLE is opened to students, demographic data are the only information available for the analysis. After the students start interacting with the VLE system, the weight of the demographic data diminishes and VLE data become the major predictor of students' success.

This can be illustrated using a simplified example depicted in Figure 2. The model on the left predicts the success in the next assessment only from demographic data while the model on the right adds the data from VLE.

Figure 2: Predictions using a) only demographic data, b) demographic data and VLE.

To demonstrate the impact of VLE we selected the following classes of demographic attributes:

1. New student, Male, No formal qualification,
2. New student, Female, A level or equiv.
3. Continuing student, Female, A-level or equiv.
4. Continuing student, Female, HE qualification
5. Continuing student, Male, Postgraduate qualification.

Table 1 shows that for all five cases, the probability of failure changed significantly when augmented with VLE attributes. In this simple example, VLE activity types are not taken into account. By failure we mean that either the student did not submit the assessment or submitted but scored below 40 points out 100 points maximum.

For example, in Case 1 if the model is built only from demographic attributes, the probability of failure is about 18%. If the VLE activities are considered the probability of failure is dramatically affected. If the students didn't participate in the VLE, this probability goes up to 64%. On the other hand, for highly active students from the same group (clicks >= 101) this probability dropped to 6.3%. This pattern holds in all presented cases.

Attributes	Probability of failure				
	Case 1	Case 2	Case 3	Case 4	Case 5
Demographic only	18.5%	7.7%	6.0%	4.5%	5.0%
Demo and clicks = 0	64.0%	39.0%	33.0%	26.0%	31.0%
Demo and clicks = 1-20	44.0%	22.0%	18.0%	14.0%	15.0%
Demo and clicks = 21-100	26.0%	11.2%	9.0%	7.0%	7.0%
Demo and clicks = 101-800	6.3%	2.4%	1.8%	1.0%	2.0%

Table 1: Impact of VLE data

Predictive models used for predictions work with VLE data semantically enriched by the activity type label. The weekly summaries of VLE data are divided into groups according to activity types used within selected modules. Different activity types correspond to different types of educational resource used in the learning process. The "dictionary" of activity types contains many labels, however the courses typically use only 10-20 of them. By analysing legacy data it can be shown that some are more important than the others and this differs from course to course.

Predictive modelling

Identifying module fingerprints

We have developed a technique based on Bayesian analysis that identifies the most important VLE activity types for each course. The method is illustrated in Figure 3, which shows probability of

success for students that were inactive in *forum* in the two different courses denoted as XYZ and ABC in the first weeks of the spring semester 2013. The first column from the left shows the percentage of inactive and successful students in the *week 0*, the second column students that were inactive both in week 0 and 1 etc. The graph then shows that 73% of those students who were inactive in week 0 failed the course XYZ and this number goes up to 86% for those students who were inactive in all the first four weeks.

Given this example, it is clearly visible that the importance of the forum activity type is high for XYZ. On the other hand, in Figure 3 we can observe significantly lower impact of forum on course ABC. This is caused by different design and content of each course and demonstrates the need for performing the analysis of important activity types separately for each course.
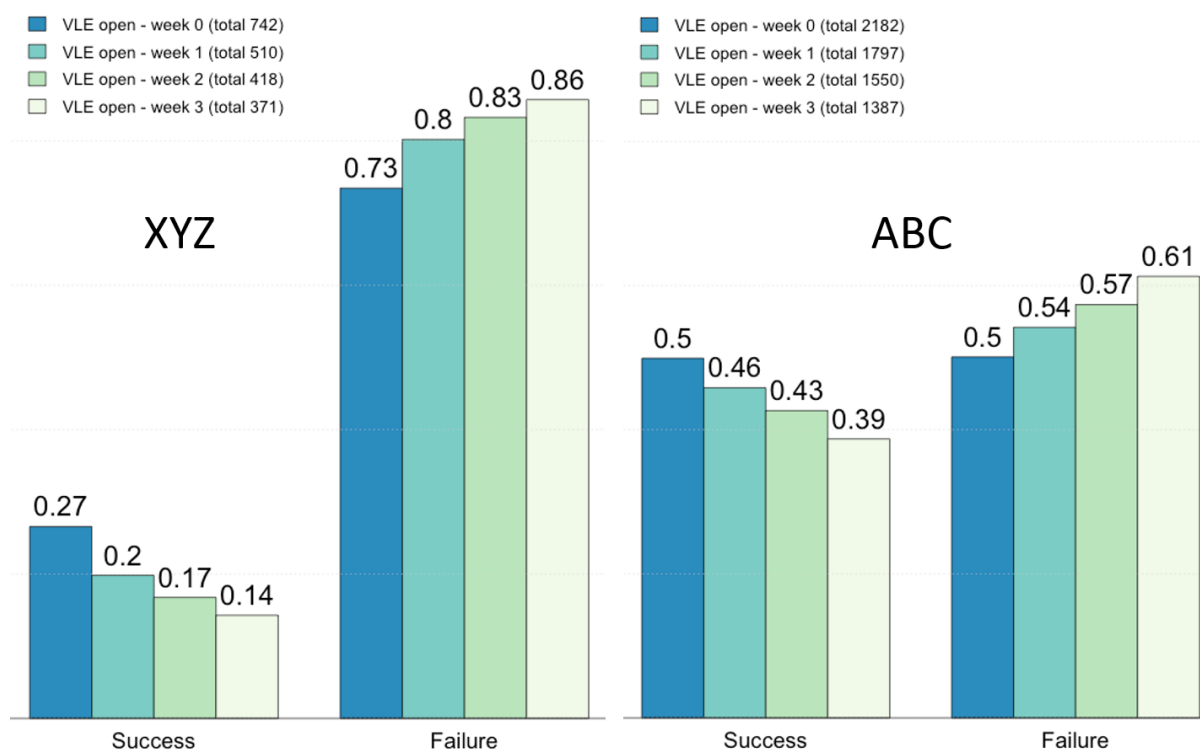

Figure 3: Probability of student's success and failure in XYZ and ABC for the students that were inactive in the forum in the first three weeks.

Predictive models

The module fingerprint, demographic data of the students and their VLE activities are used to build four predictive models: k-Nearest Neighbours algorithm, which is run separately using the demographic data and the VLE data; Classification and Regression Tree and probabilistic naïve Bayes model which uses both VLE and demographic data. The final decision is then achieved by voting, where initially each of the four models has equal weight. The process is depicted in Figure 4.
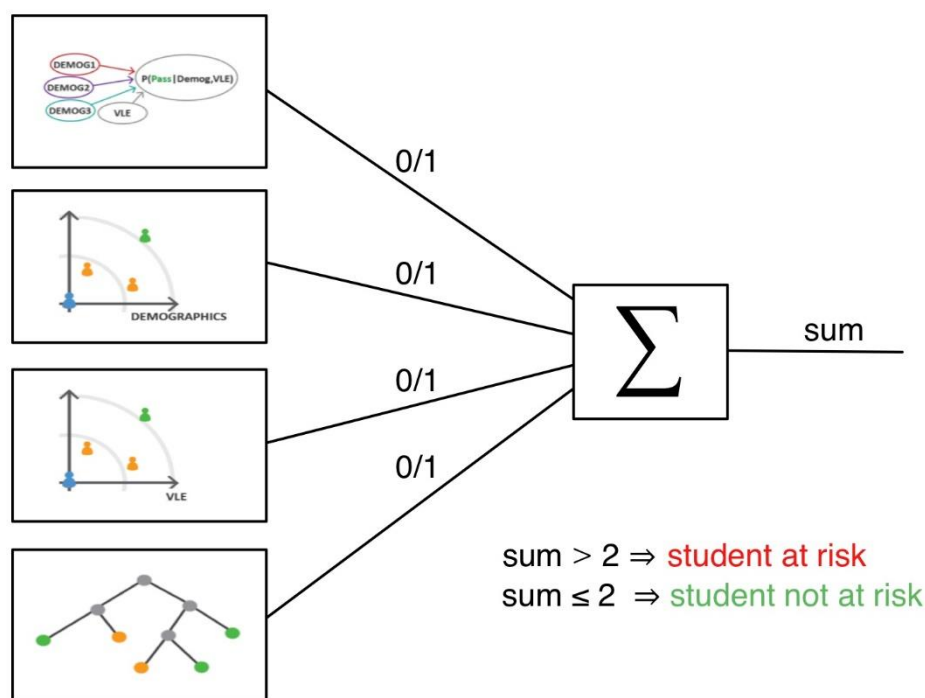
Figure 4: Voting of prediction models. Students with more than 2 votes are selected as at-risk.

Each model has been selected due to its specific properties:

- Naïve Bayes model makes decisions that are the most probable making the model average error as small as possible (Duda, et al., 1973).
- k-NN enables easy identification of the most similar students from previous presentations based on either VLE activity or on demographics. The error of k-NN is at most twice as large as Naïve Bayes error (Duda, et al., 1973).
- The CART method produces an easily interpretable set of rules converted into decision tree. Another advantage of CART algorithm is that the algorithm is able to work with numerical attributes not only with categorical attributes (Breiman, et al., 1984).

These models have been in use since spring 2014 as the basis of the weekly at-risk student predictions, initially in two courses. Currently (in autumn 2014 and spring 2015) they are deployed in 18 courses.

Evaluation of predictions

The results of evaluating the predictions done in the spring 2014 courses are depicted in the following two tables — Table 2 for course XYZ and Table 3 for course ABC. As time flows and more data become available, the precision increases. On the other hand recall – the proportion of at-risk students identified, is decreasing. The increasing precision and decreasing recall is affected by the heuristic approach incorporated in predictions, which takes into account the limited resources for interventions. The prediction models' votes are taken into account and only students with the largest number of votes, i.e. the most vulnerable ones, are included in the weekly predictions list. This leads to the decrease of recall and F measure.

Milestone	Precision [%]	Recall [%]	F measure [%]
assessment 1	47.6	52.9	50.1
assessment 2	68.7	49.3	57.4
assessment 3	80.3	37.5	51.1
assessment 4	85.7	25.0	38.7

Table 2: XYZ prediction results

Milestone	Precision [%]	Recall [%]	F measure [%]
assessment 1	69.5	34.1	45.8
assessment 2	88.5	15.6	26.5
assessment 3	83.8	19.7	31.9
assessment 4	93.4	20.7	33.9

Table 3: ABC prediction results

OU Analyse dashboard - weekly predictions of at-risk students

Following the data collection and the development of the first predictive models, a prototype of an online dashboard for presenting the results of the predictive models has been designed. The underlying idea for developing the dashboard was to allow the course teams to always have access to the most up-to-date predictions. The dashboard also provides a filter that returns only students satisfying selected criteria (for example using demographic information of students) and allows exporting the selected list as an Excel spreadsheet file. The prediction list includes detailed information about selected students and makes it possible to track their progress individually. Furthermore, in order to allow different stakeholder groups to use the dashboard, the application supports a number of user roles with different access rights.

The pilot version of the dashboard is depicted in Figures 5 and 6. Figure 5 shows the course view page. This page displays overview information of one course presentation. There are two main components on the page — an *overview* of student activity in the VLE together with average assessment results and a *table* with results of individual students and their predictions for the next assessment. The VLE activity and results or assessments are compared with previous course presentation. In addition, the page displays several overview statistics, such as assessment submission rate for the last assessment or the number of students active in VLE during the past week.

Figure 5: OU Analyse dashboard — course overview page.

Figure 6 shows the student overview page. One of the main components of the page is the VLE activity of the selected student and his/her assessment scores, which are compared with the activity and average assessment scores of the cohort. The student overview page also shows details of student assessment results along with the predictions and their justifications, the graph showing the "nearest" students and student activity recommender.

The nearest students are those who studied the current and previous presentations of the course and who are the most similar to the given student based on demographics and VLE criteria. The target graph contains the selected student in the centre. The nearest students can be adjusted by giving different weights to the demographic and VLE data. The colour coding of the nearest students show whether they have passed, failed or withdrawn the course. By clicking on a nearest student icon his/her data are retrieved, the student is located in the centre and can be investigated in detail.

The student activity recommender in the bottom of the page lists personalised selection of VLE resources, which the student hasn't yet interacted with and which are likely to be the most important for his/her success in next assessment.

Figure 6: OU Analyse — student overview page.

Current work

The analysis and all the work related to weekly predictions in spring semester 2014 was done for the two pilot courses. With the beginning of the fall semester 2015, the number of the analysed courses went up to 18 different courses, which brought new challenges.

Scaling up

For the two courses, the whole analysis process could be run manually. This includes 1) retrieval of the data related to the current and previous presentation of the course in the current week, 2) data pre-processing, 3) learning the models from legacy data, 4) computing the predictions along their justifications and 5) preparing the results in the form of Excel spreadsheet for the convenience of the course team. However, with the increased number of the courses in the autumn and spring semester and the vision of possibly scaling up to all OU courses, it was necessary to redesign the whole process to be automated as much as possible.

As soon as the VLE activity data from the previous day are available, they are imported into the OU Analyse system and transformed for future processing. One of the most critical and time-consuming parts of the analytical process is the cleaning, integration and pre-processing of the raw data. The database that stores the source data is very complex and many transformation procedures have been implemented to prepare the data for learning the predictive models. Although the structure of the analysed courses is similar, differences exist and the process has not yet been fully automated.

The next challenge was to automate the process of identification of the activity types available in the current week, which are important for the next assessment. Again, when doing this for two courses, we were able to perform the task by manual inspection of results from Bayesian analysis. We are currently investigating a procedure that does this task automatically. This procedure is based on the Minimum Redundancy Maximum Relevance algorithm (Peng, et al., 2005). In addition to the automation of the selection of the most important features with respect to the predicted class, the algorithm minimises the redundancy among the selected features.

Currently the machine learning models are trained sequentially, because the number of the courses is not too high to otherwise delay the delivery of the predictions. However, with the growing number of the courses under analysis, there will be a need to optimize the training phase in the future.

Currently, the predictions are sent to the course teams via email. To speed up the delivery of the results, the predictions will be available in the dashboard application after the prediction computation finishes. Moreover, the dashboard provides additional features to support exploration of the results.

The predictions are currently computed weekly, but as soon as the process is automated, we will be able to deliver the predictions more often, possibly even every day. It is worth mentioning that even though the whole process is already almost fully automated, some of the tasks still need to be done manually. Fortunately, these tasks are usually important only before the course starts and they do not slow down the process later.

New courses without history

Predicting at-risk students for new courses without any historical data available is another challenge we are facing. The problem can be divided into two:

- Predicting at-risk students in a new course for which a similar predecessor exists.
- Predicting at-risk students in a completely new course, which has no similar courses in the history.

The first problem can be solved by mapping a similar historical course to the new one and using the historical course as a source of legacy data. The key issue is the mapping of assessments, course content and VLE interactions from the old course to the new one. This model defining process requires the support of the course design team.

The solution to the second problem is not as straightforward as the first one and an optimal solution does not exist. Still there are various methods, which make it possible to perform predictive modelling even for these courses. First approach involves ontological modelling of typical course

structures, which then leads to finding the most similar course from the university portfolio and applying the previously mentioned method.

When the ontologies cannot be found or the course has so specific structure that it cannot be mapped to any available course there is still a chance to use results from previous assessment block of the course to predict at-risk students for future assessment blocks of the same presentation. In other words the prediction models use the courses own "legacy data" for predicting its 'at-risk' students. This method has been tested and seems to produce encouraging results.

Predicting not only success/failure label

Courses with high retention, for example second and third year courses taken by students who are closer to the completion of their degree, are often focused more on improving student grades rather than on improving retention. Tutors and students of these courses are therefore interested in improving assessment results and consequently the final result of the course. Prediction models can be extended to provide also information about the expected mark of the next assessment. The challenging issue is to predict the final result based on the student's results achieved so far and the prediction of the upcoming assessment. The solution gives weights to all previous assessments and then infers the final result.

Lack of sufficient information

We explained the importance of the early identification of the at-risk students. One of the challenges of identifying at-risk students as early as possible lies in insufficient data in the beginning of the course (at the beginning of the course we don't have data characterising student's activities). In such a case, we utilise the demographic information, which provides a crude estimate of success or failure. We explored some of the possibilities for tackling this problem, such as influence of participation of the students in an introductory course before they start studying their degree. Although there was no statistical significance showing that this participation is important for the student's success, it may be interesting for some other courses. Extending the scope to all the previous courses might be of interest; however for level one courses, these data are not available. Several other interesting ideas exist which are worth exploring and the problem still remains open.

Conclusions

Building predictive models for identifying at-risk students using machine learning techniques and student activity data recorded in previous presentations of the same course proved to provide useful information for course teams and tutors. Since the data record all interactions of each student with VLE, it is easy to find the learning material that the student has missed. If the student has been identified as at-risk, it is possible to recommend the resources that can bring him/her back on track. Predictions of at-risk students also help the student support teams to focus the interventions on specific needs of each individual. The OU Analyse dashboard with a course view and student view provides flexible and easy access to the predictions and makes it possible to scale up this approach. A number of challenges, such as different course prediction needs or varying number of weeks in previous presentations and different ordering of assessments, still exist. These challenges often stem from changes in course design and need to be addressed on a course by course basis. Furthermore, experiments are currently being carried out to use a similar approach on data from conventional universities.

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Wolff, A., Zdrahal, Z., Herrmannova, D. & Knoth, P., 2013. Predicting student performance from combined data sources. In: A. Peña-Ayala, ed. *Educational Data Mining: Applications and Trends.* Verlag: Springer International Publishing, pp. 175-202.

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About this Paper

Acknowledgements

Citation details

About the Authors

Jakub Kuzilek is Research Associate at the Open University, UK and also Research Assistant at the Czech Technical University, CZ. He is the member of OU Analyse project and his professional interests include machine learning, signal processing and learning analytics.

Martin Hlosta is a Research Assistant at Knowledge Media Institute at The Open University and PhD student at Faculty of Information Technology, Brno University of Technology, where he received his master's degree in Computer Science in 2010. His current research interests include data mining methods in learning analytics and learning from imbalanced data.

Drahomira Herrmannova is a Research Student at the Knowledge Media Institute, Open University. Her research interests include bibliometrics, citation analysis, research evaluation and natural language processing. Aside of her PhD she participated in research projects at the Open University (CORE, OU Analyse).

Zdenek Zdrahal is Professor of Knowledge Engineering at the Open University, UK and Associate Professor at the Czech Institute of Informatics, Robotics and Cybernetics, Czech Technical University. At the Open University, he leads the OU Analyse project. His professional interests include learning analytics, machine learning and knowledge sharing.

Jonas Vaclavek is a student of Bachelor program of Open Informatics at the Czech Technical University in Czech Republic. He works as an intern at The Open University where he is a member of OU Analyse team. His job is to maintain and innovate project's front-end.

Annika Wolff is a researcher in the department of Maths, Computing and Technology at the Open University. Her research interests include learning analytics, learning technologies, narrative, games, hypermedia, mobile-learning and Smart City technologies.

Licence

About the Learning Analytics Review

Background

The Learning Analytics Review provides a series of stand-alone series of articles aimed primarily at people who want to make decisions about what they are going to use learning analytics. While they will be of an authoritative and scholarly character, they will generally be white papers or briefings.

The white papers and briefings are complemented by additional papers related to various aspects of learning analytics which will be of interest to the broad learning analytics community.

About this Learning Analytics Review Paper

To support the LACE project's community-building work a series of three papers have been published based on sessions which were presented at the LAK 15 conference. These are:

1. Kuzilek, J., Hlosta, M., Herrmannova, D., Zdrahal, Z., and Wolff, A. OU Analyse: Analysing at-risk students at The Open University, *Learning Analytics Review*, Paper LAK15-1, ISSN 2057-7494, March 2015, *http://www.laceproject.eu/learning-analytics-review/analysing-at-risk-students-at-open-university/*
   This paper was presented on Wednesday 18th March 2015 in the Students At Risk session and on Thursday 19th March 2015 in the Technology Showcase session.
2. Vovides, Y., Arthur, P., Pongsajapan, R. and McWilliams, M. Examining Learners' Cognitive Presence Through Linguistic Analysis in Massive Open Online Courses, *Learning Analytics Review*, Paper LAK15-2, ISSN 2057-7494, March 2015, http://www.laceproject.eu/learning-analytics-review/examining-learners-cognitive-presence-in-moocs/
   This paper was presented on Wednesday 18th March 2015 in the MOOCs—Discussion Forums (Practitioner) session.
3. Grann, J. Flexpath: A Case Study in Building Competency-based, Direct Assessment Offerings, *Learning Analytics Review*, Paper LAK15-3, ISSN 2057-7494, March 2015, *http://www.laceproject.eu/learning-analytics-review/building-competency-based-offerings/*
   This paper was presented on Thursday 19th March 2015 in the Learning Strategies and Tools (Practitioner) session.

About the LACE Project

The LACE project brings together existing key European players in the field of learning analytics & educational data mining who are committed to build communities of practice and share emerging best practice in order to make progress towards four objectives.

> *Objective 1 – Promote knowledge creation and exchange*
> *Objective 2 – Increase the evidence base*
> *Objective 3 – Contribute to the definition of future directions*
> *Objective 4 – Build consensus on interoperability and data sharing*

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