Prediction of Learning Success Via Rate of Events in Social Networks for Education

M. E. Sousa-Vieira, J. C. López-Ardao, M. Fernández-Veiga, O. Ferreira-Pires and M. Rodríguez-Pérez

Department of Telematics Engineering, University of Vigo, Spain

Keywords: Online Social Networks, Collaborative Learning, Learning Analytics, Success/Failure Prediction.

Abstract: The widespread use of computing and communications technologies has enabled the popularity of social networks oriented to learn. Earlier studies have shown the power of online learning systems data to develop prediction methods that try to identify successful students patterns of accomplishment and engagement to allow timely pedagogical interventions. Our learning platform, SocialWire, collects a detailed record of the students' activity so, in this paper, we compare and combine the power of different statistical learning techniques, using some of the features recorded as predictors of learning success or failure.

1 INTRODUCTION

Information technology is changing the ways we learn. The widespread use of computing and communications technologies has enabled the formation of personal communications or online social networks (OSNs), and it is behind the popularity of social networks oriented to learn (Vassileva, 2008; Hart, 2011).

Effective methodologies for social learning rely on two essential components: (i) a properly designed software platform which integrates contents, users and educational experiences in a productive social learning environment (SLE); (ii) an understanding of how the social learning activities have to be designed so as to improve the experience and quality of the learning outcomes of students. For the first part, since popular management systems (LMSs) do not offer full functionality for embedding online social network (OSN) features adequate to our purposes, recently we have developed our own learning platform, SocialWire (Sousa et al., 2016). For the second requirement, it is necessary to apply learning analytics (usually based on social networks analysis or machine learning methods) in order to understand the effects of the methodology on students' performance.

In this work, we address these two issues. We describe SocialWire (SocialWire), a SLE which has been purposely designed to provide a complete social learning paradigm, including features not available in other learning environments. Beyond the typical features of a LMS related to online formal learning, Socialwire allows the creation, assessment and reporting of a range of collaborative activities based on social interactions among the students, offering reward mechanisms by means of ranking and reputation. Moreover, custom-made plugins collect detailed records of the students' and teachers' activity while they are engaged in the system.

These data can be used to analyze the individual behavior of users for identifying the behavior patterns that lead to success in learning (Lykourentzou et al., 2009; Macfadyen and Dawson, 2010; Brinton and Chiang, 2015) or to quantify how the information flow shapes the learning results, discovering the most influential students or finding out how collaboration among groups of students arise and the impact of the relationships on learning performance (Laat et al., 2007; Cadima et al., 2012; Hommes et al., 2012; Chung and Paredes, 2015; Skrypnyk et al., 2015; Eid and Al-Jabri, 2016; Sousa et al., 2017b; Sousa et al., 2017a). Taking into account these findings, learning failure prediction methods can be implemented to allow timely pedagogical interventions.

In this paper we report our experience using SocialWire during two consecutive years of a computer networking course directed to undergraduates of the second year of the Telecommunications Engineering degree. We describe the methodology employed along the course and we propose a learning success/failure prediction method that combines the power of different statistical learning techniques using some of the features of the student's activity al-

Sousa-Vieira, M., López-Ardao, J., Fernández-Veiga, M., Ferreira-Pires, O. and Rodríguez-Pérez, M.
Prediction of Learning Success Via Rate of Events in Social Networks for Education.
DOI: 10.5220/0006780703740382
In *Proceedings of the 10th International Conference on Computer Supported Education (CSEDU 2018)*, pages 374-382
ISBN: 978-989-758-291-2

ong the course as predictors.

The rest of the paper is organized as follows. In Section 2 we give an overview of the core social engine, and describe the general principles of our learning-enhanced social platform. The methodology employed in a real testbed (two consecutive editions of an undergraduate course on Computer Networks) is reported in Section 3. Section 4 contains the main results of the data mining applied to our datasets. The proposed success/failure prediction methods are explained in Section 5. Finally, concluding remarks and guidelines for further work are included in Section 6.

2 THE LEARNING PLATFORM

Socialwire (Sousa et al., 2016) is a SLE purposely designed to provide a complete networked learning paradigm, including features not available in other SLEs. For instance, Socialwire uses games and social meritocracy as conducting threads. The software platform is based on ELGG (Elgg), a popular engine for developing OSNs, and allows the creation, assessment and reporting of a range of collaborative activities based on social interactions among the students, offering a reward mechanism by means of ranking and reputation.

The platform was developed upon four blocks:

- The online social network. SocialWire leverages on the core of ELGG for reusing the fundamental elements of a generic OSN. Every group (classroom group) defined in the system has its own wall to maintain open communication among all its members. The group can also use common tools in the social web for its virtual classroom activities: classroom blog, collaborative publishing and document editing, creation of web pages, social tagging, files repositories with hierarchical structure (including a viewer for images, audio, video and the usual document formats), and event calendars. All the activity unfolded in the classroom gets eventually reflected on the public wall, so it can be commented, highlighted or voted. Sharing videos, uploading a file, save and send a link are extremely simple actions which the user can invoke through an user interface deliberately similar to an OSN user interface. The user-friendliness is higher, as a bonus, and the learning curve of the platform itself is greatly softened.
- The formal learning processes. To furnish SocialWire with the usual features of a LMS, we have developed custom software modules that extend the bare OSN based on ELGG. Specifically, there exist modules for proposing and submitting tasks (either online or offline), for the creation and assessment of quizzes and questionnaires, for the creation and processing of forms or polls, for building an e-portfolio, for designing rubrics for evaluation, and more. Another software module gives the teachers the possibility of structuring the learning units in their courses, for instance weekly, monthly, by topic,... and adding to each unit as many resources as they like.
- The informal learning processes. SocialWire opens the possibility of carrying out other sort of activities requiring a higher degree of social interaction. This is done by means of the questions and answers module and the contests module. Besides the usual grading procedure used in formal courses (on a numeric scale or by discrete levels), in SocialWire the students can receive "points" or "marks" for their works. The points accumulated along the course determine their position in the students' ranking. This ranking serves primarily to send behavioral signals to the students about their relative performance, in a way that directly stimulates comparisons and that automatically conveys the meaning of social reputation.
- The collaborative work processes. Most of the popular software platforms for collaborative work fail to give real, effective support for working collaboratively. First, the users are not given a virtual workspace where direct communication and sharing between colleagues can happen, so they must resort to external programs to solve this (or in extreme cases, physical meetings). Secondly, teachers are not provided with the opportunity to manage, coordinate, assess, evaluate, share or communicate with the workgroups. SocialWire does permit subgroups, i.e., smaller groups within an existing group. The instructors are in charge of deciding how many groups will be created, their sizes and their membership policies, if any is due. Every activity supported by SocialWire can be assigned to a group or to an individual, and in the former case any group member is entitled to participate in the role of group's representative. Additionally, every subgroup is internally a group and has a private space so that their members and the instructors can communicate.

For the goals of this paper, two of the plugins of SocialWire are of key importance. These are the event collector plugin, and the event viewer plugin. The first is a plugin that runs in the background and records all the relevant activity of the students (and teachers too), both the interactions between an user and the learning objects stored in the platform and the interactions between two users. Every possible action by an user of SocialWire is logged as an event in a format compliant to the TinCan standard, so that a full Learning Record Store (LRS) of the user's activities can be easily reconstructed. This entails a structure of the form Subject+Verb+Object for every event, where the user is the subject and the possible verbs (actions) are `login`, `follow`, `create`, `update`, `remove`, `response`, `comment`, `uncomment`, `like`, `unlike`, `upload`, `download` and `view`. The second plugin is a graphical viewer for the set of LRSs stored in the platform, with features for plotting graphs or trends, and also for filtering the collection of events according to multiple criteria. As an illustration, Figure 1 reproduces a screenshot of the activity logs, and an example of the viewer —a histogram of the number of interactions of a student with each resource type along the course— appears in Figure 2.

3 APPLICATION

The SocialWire platform has been used to teach one computer networking course over several consecutive academic years. In this work we consider the 2015/2016 and 2016/2017 editions. The course is directed to undergraduates of the second year of the Telecommunications Engineering Degree, and has a weekly schedule that lasts 14 weeks.

Lectures are organized as follows:

- A two-hour in-class lecture, that mixes descriptive content (the Internet architecture, basic principles and concepts, anatomy of the main protocols) with some elementary mathematical details for analyzing network performance.
- A two-hour laboratory session, in small study groups. This is a complementary session where the students solve written exercises, work with real networking equipment and make a small programming assignment.

The students (and teachers) belong to a single group in SocialWire, wherein general communication about the topics covered takes place. To encourage networked learning activities and collaborative work, each year the teachers plan different activities in SocialWire whereby the students may gain points (the resulting ranking is made public to the group). In the two editions considered in this work three types of online activities were proposed:

- Tasks previous to the in-class or the laboratory sessions. By means of this activity teachers successfully encourage the students to prepare some of the material covered in the in-class or the laboratory sessions in advance.
- Quizzes previous to the partial exams. Quizzes are just practice exams for self-training.
- Collaborative answering of questions. This activity consist on posing and solving questions or doubts about the subject. The students can send their questions, an so do the instructors occasionally. Each apt answer gets a number of points that depends on its quality, completeness and also of the difficulty of the question. Teacher can reward the timeliness in answering a question,too.

Face-to-face interaction (in the classroom and in the laboratory session) is still the bulk of the course, for a total of 50 hours. But the social networking activities occupy a significant fraction of the independent study time by the students (an average of 10-12 hours is spent in the online activities by the students, though there is a wide variability). More importantly, there is actually a connection between the more formal face-to-face learning activities and the online tasks, in that many discussions and homework problems start in the classroom but take place further through the online platform, and are finished there.

Though this subject may be passed with a single final examination covering all the material (and if the programming assignment meets the minimum requirements), students are encouraged to follow the continuous assessment path. In the two academic years, the weight of the continuous assessment was 40%, and the remaining 60% being awarded as the result of a final exam held on two different dates (last week of May and first week of July, non-exclusive). The continuous assessment weight is split into a 10% for the programming assignment, a 20% from the partial exams and a 10% of the final grade comes out from the game points gathered by engaging in the social activities commented previously to increase the level of participation. While it is true that one point in the final grade might seem a too scarce pay off for the best student, we believe it is important that the full score is easily achievable by a significant fraction of the class. Thus, in order to convert the point marks into a grade, if P_{av} is the average number of ranking points per student and $P_{\max}$ is the maximum, we compute $M = \min\{P_{\text{av}}, P_{\max}/2\}$. In the conversion scale, M represents 0.5 grade points, and every student having at least $2M$ game points gets the full 1 grade possible with this part. In doing so, we try to preserve the incentive-driven effect whereby the average-performing student is still engaged and the best students attain due pay offs.

In Table 1 we show some data related to the cohorts of students involved in the study, the size of the

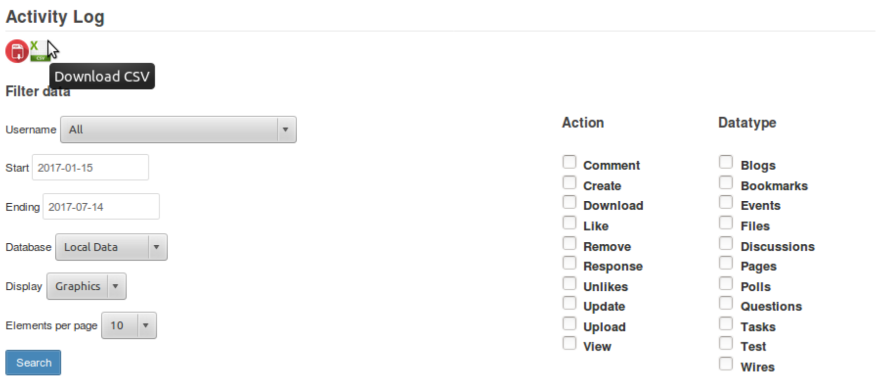

Figure 1: Screenshot of the events collector plugin (filtering of activities in the SLE platform).

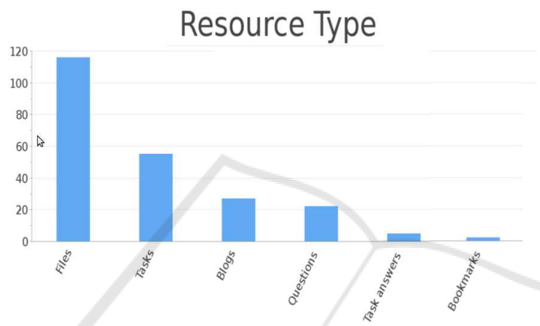

Figure 2: Screenshot of the events collector plugin (number of interactions of a student with the learning resources).

cohort, the number of second-taking students and the number of students that participated in the activities scheduled for continuous assessment.

4 ANALYSIS OF THE DATASETS

Although we have a detailed record of all the student's activity related to the course, we have analyzed some features which could be related to the students' ultimate performance at the end of the course.

- ST: Second-taking (or not), i.e., whether the student has previously taken this course or is a freshman.
- CA: Continuous assessment (or not), i.e., whether the student chooses continuous assessment during the term rather than a single examination at the end.
- GP: The total number of points received in the tasks, quizzes and answers to the questions posed through the platform.
- RC: A variable keeping track on whether the student watches the learning resources companion to the lectures (for instance, slides, short videos, tutorials, etc.)
- RL: An analogous variable, this time for the activity of watching learning resources specifically prepared for the laboratory sessions (e.g., reading the manuals, downloading the software tools, etc.)
- RT: The student reads the tasks.
- RP: The student reads the documents and resources which are necessary for completing the programming assignment.
- RE: The student reads the solutions of partial exams.
- SE: Slope of all the events related to any part of the course. In addition to the already mentioned events —which have been covered by the variables above— this also includes events such as reading some blog article, or reading some news with content related to the topics of the course. The slope is simply the number of events per unit time.

In order to select the features most correlated with the achievements of the course, we have carried out two statistical tests.

First, we measured the statistical correlations between the features under study and the final grades obtained in the subject. The sample correlations $\hat{\rho}$ were computed and the linear regression statistical test was used to quantify such correlations. This test

Table 1: Cohorts data.

Academic years 2015/16 - 2016/17		
Size	Second-taking	Continuous assessment
180 - 182	82 - 92	168 - 176

Table 2: Correlation between features and student's performance.

	Academic years 2015/16 - 2016/17	
	$\hat{\rho}$	$(\hat{\beta}, t, \mathbb{P}(>\lvert t\rvert))$
ST	0.0186 - 0.1551	$(0.0709, 0.2491, 8.041 \cdot 10^{-1})$ - $(-0.6632, -0.2107, 3.651 \cdot 10^{-2})$
CA	0.2831 - 0.1891	$(2.1518, 3.9391, 1.171 \cdot 10^{-4})$ - $(2.1031, 2.5851, 1.053 \cdot 10^{-2})$
GP	0.5231 - 0.7253	$(0.0895, 8.1882, 4.982 \cdot 10^{-14})$ - $(0.0841, 14.1371, 2.001 \cdot 10^{-16})$
RC	0.0696 - 0.1563	$(0.0055, 0.9312, 3.531 \cdot 10^{-1})$ - $(0.0125, 2.1241, 3.501 \cdot 10^{-2})$
RL	0.2039 - 0.3234	$(0.0228, 2.7791, 6.042 \cdot 10^{-3})$ - $(0.0642, 4.5861, 8.431 \cdot 10^{-6})$
RT	0.3577 - 0.4842	$(0.0358, 5.1121, 8.191 \cdot 10^{-7})$ - $(0.0667, 7.4271, 4.301 \cdot 10^{-12})$
RP	0.3299 - 0.5141	$(0.0306, 4.6641, 6.071 \cdot 10^{-6})$ - $(0.0492, 8.0401, 1.161 \cdot 10^{-13})$
RE	0.3311 - 0.3424	$(0.0779, 4.6822, 5.631 \cdot 10^{-6})$ - $(0.0705, 4.8892, 2.231 \cdot 10^{-6})$
SE	0.3764 - 0.5401	$(0.1041, 5.4221, 1.901 \cdot 10^{-7})$ - $(0.1977, 8.6083, 3.631 \cdot 10^{-15})$

quantifies the statistical significance of a linear fit of a response variable on one factor variable. The estimated linear coefficient is denoted by $\hat{\beta}$. Under the null hypothesis (meaning that there is no such linear dependence) the test statistic follows a t-distribution and high values are very unlikely (Hastle et al., 2008). As we can see in Table 2 there is a significant positive dependence between almost all the considered factors, namely GP, RL, RT, RP, RE, and SE and the students' performance. Actually, the correlation for ST for the subset of data corresponding to the 2015/2016 edition is almost zero, whereas it is negative for the subset of data taken for the 2016/2017 edition. This confirms that many of the students who take the course for a second time perform clearly better. The low values obtained for the variable RC are not surprising, after all, since the learning resources which go along the lectures are commonly read and downloaded by nearly all the students. And the low values for the variable CA are due to the fact that an overwhelming fraction of the students prefer the continuous assessment option, especially in the academic year 2016/2017.

Second, we measured the correlation between the features under study on the students who pass or fail the subject. To answer this question, we applied the Smirnov's statistical test. This is a classical hypothesis test for comparing the equality between two probability density functions, or its lack of equality. Specifically, under the null hypothesis that the two distributions (students who pass/fail) are equal, the value of the Smirnov's statistic follows a known distribution. In that probability distribution, values of the p-value greater that the level of significance (5%) do not allow to reject the equality hypothesis (Hastle et al., 2008). In view of the results shown in Table 3, equality between the two distributions is rejected in both editions in GP, RL, RT, RP, RE and SE.

Table 3: Significant differences between the features of students that pass or fail the subject.

	Academic years 2015/16 - 2016/17
	(D, p-value)
ST	$(0.1257, 4.926 \cdot 10^{-1})$ - $(0.1181, 5.828 \cdot 10^{-1})$
CA	$(0.0634, 9.943 \cdot 10^{-1})$ - $(0.0524, 9.998 \cdot 10^{-1})$
GP	$(0.4577, 1.803 \cdot 10^{-8})$ - $(0.6035, 4.008 \cdot 10^{-14})$
RC	$(0.1795, 1.159 \cdot 10^{-1})$ - $(0.2688, 3.821 \cdot 10^{-3})$
RL	$(0.2293, 1.921 \cdot 10^{-2})$ - $(0.2761, 2.714 \cdot 10^{-3})$
RT	$(0.3681, 1.262 \cdot 10^{-5})$ - $(0.4243, 3.384 \cdot 10^{-7})$
RP	$(0.2971, 8.156 \cdot 10^{-4})$ - $(0.5015, 6.968 \cdot 10^{-10})$
RE	$(0.2881, 1.301 \cdot 10^{-3})$ - $(0.4232, 3.679 \cdot 10^{-7})$
SE	$(0.3627, 1.775 \cdot 10^{-5})$ - $(0.5922, 1.292 \cdot 10^{-13})$

The results obtained in both cases suggest that GP, RL, RT, RP, RE, SE are highly correlated with the achievements in the course and could be good predictors of the student's grade. Or, in the reverse direction, that few or no participation in the social platform by a student could be an early alert of bad learning results. In Section 5 we explain how these features are used in this work to build learning success/failure prediction methods, based on popular statistical learning techniques.

5 LEARNING SUCCESS/FAILURE PREDICTION

To check the power of the above selected measures to predict students success/failure, we have considered three popular statistical learning classifiers (Han et al., 2012), namely logistic regression (LR), linear

Table 4: Performance results of thecombined technique.

		2015/16	2016/17	2015/16 → 2016/17	2016/17 → 2015/16
Accuracy	GP+RL+RT+RP+RE+SE	0.7804	0.9077	0.7945	0.9196
	GP+PE	0.7955	0.9111	0.8001	0.9057
	PE	0.8737	0.9276	0.8674	0.9208
Sensibility	GP+RL+RT+RP+RE+SE	0.8233	0.9344	0.9159	0.9826
	GP+PE	0.8478	0.9442	0.8899	0.9658
	PE	0.9977	0.9985	0.9999	0.9993
Precision	GP+RL+RT+RP+RE+SE	0.7847	0.9131	0.7038	0.8828
	GP+PE	0.7858	0.9092	0.7428	0.8792
	PE	0.7791	0.8825	0.7697	0.8752

discriminant analysis (LDA) and support vector machines (SVM). These classifiers function in two phases: during the training phase they are presented with a set of input-output pairs. Each classifier then adjust its internal parameters and during the testing phase they are presented with new input data to predict the outputs. If actual output values are available, the comparison with the predicted ones is used to measure the performance of the classifier.

In our application, the training sets consist of the selected student data of the two offerings of the course considered in the study (we have selected these datasets due to the high similarities in the methodology along the whole term in both offerings). The output is the binary variable that represents the success or failure of the students in the course, and the input is a combination of some of the features described in the previous section.

We use k-fold cross validation to consider multiple training/testing set partitions. If the set of observations is the same for training and testing, this approach involves randomly divide it into k groups of approximately equal size. The procedure is repeated k times and each time $k-1$ different groups of observations are treated as the training set and the other one as the testing set. If one set of observations is used for training and another different for testing, the first one is divided into k groups of approximately equal size and in each repetition of the procedure $k-1$ different groups are treated as the training set. In any case, as this procedure results in k values, the performance results are computed by averaging these values. We have selected $k=5$ in our proofs and, in order to increase the accuracy, we have repeated the procedure 10 times, being the final performance values obtained by averaging again the 10 resulting values.

To evaluate the performance of decision we have used three different criteria, which estimate the accuracy, the sensitivity and the precision. We consider the following notation: PF the predicted failures, PS the predicted successes, TPF the correct predicted failures, TPS the correct predicted successes, FPF the incorrect predicted failures and FPS the incorrect predicted successes.

The accuracy criterion measures the total proportion of the students whose final status, failing or passing the course, was correctly predicted

$$\text{Accuracy} = \frac{\mathsf{TPF}+\mathsf{TPS}}{\mathsf{PF}+\mathsf{PS}}.$$

The sensitivity criterion measures the proportion of the students whose final status, failing (or passing) the course, was correctly predicted

$$\text{Sensibility} = \frac{\mathsf{TPF}}{\mathsf{TPF}+\mathsf{FPS}} \text{ or } \text{Sensibility} = \frac{\mathsf{TPS}}{\mathsf{TPS}+\mathsf{FPF}}.$$

The precision criterion is used to determine the proportion of the students that actually failed (or passed) the course, among all those that the method predicted as such.

$$\text{Precision} = \frac{\mathsf{TPF}}{\mathsf{TPF}+\mathsf{FPF}} \text{ or } \text{Precision} = \frac{\mathsf{TPS}}{\mathsf{TPS}+\mathsf{FPS}}.$$

In order to increase the level of accuracy, we propose a combined method where a student is considered to fail the subject if at least one technique (LR, LDA or SVM) has classified it as such. In Table 4 we show the results obtained (considering the prediction of successes). The first two columns consider the same dataset for training and testing and the last two columns consider one of the datasets for training and the other one for testing.

After testing combinations of different subsets of predictors, we found that the variable PE, i.e., the slope of the events by a student, produces the most accurate results. For that reason, in the Tables the results which were obtained by combining all the prediction factors that showed significant correlation are shown along with the outcomes for GP+PE, and for PE alone. The events rate can be tracked thanks to events collector and the viewer plugins, as mentioned, and is easy to display. As en example, Figure 3 depicts the accumulated number of events for a sample of 6 students in each academic year.

In Tables5 we show the results obtained taking into account the accumulated values of the predictors

Table 5: Performance results of the combined technique (until end of each month).

Until end of February		2015/16 → 2016/17	2016/17 → 2015/16
Accuracy	GP+RL+RP+SE	0.7727	0.7461
	GP+PE	0.8012	0.7951
	PE	0.8608	0.8746
Sensibility	GP+RL+RP+SE	0.8971	0.8849
	GP+PE	0.9079	0.9266
	PE	0.9753	0.8851
Precision	GP+RL+RP+SE	0.6829	0.6824
	GP+PE	0.7268	0.7237
	PE	0.7851	0.9243

Until end of March		2015/16 → 2016/17	2016/17 → 2015/16
Accuracy	GP+RL+RT+RP+SE	0.8249	0.8619
	GP+PE	0.7945	0.8524
	PE	0.8727	0.8676
Sensibility	GP+RL+RT+RP+SE	0.9725	0.9649
	GP+PE	0.8787	0.9293
	PE	0.9871	0.9379
Precision	GP+RL+RT+RP+SE	0.7214	0.8037
	GP+PE	0.7342	0.8269
	PE	0.7969	0.8421

Until end of April		2015/16 → 2016/17	2016/17 → 2015/16
Accuracy	GP+RL+RT+RP+RE+SE	0.7732	0.8936
	GP+PE	0.7834	0.8584
	PE	0.8523	0.9018
Sensibility	GP+RL+RT+RP+RE+SE	0.8898	0.9781
	GP+PE	0.8823	0.9519
	PE	0.9933	0.9706
Precision	GP+RL+RT+RP+RE+SE	0.7032	0.8474
	GP+PE	0.7178	0.8069
	PE	0.7514	0.8692

Until end of May		2015/16 → 2016/17	2016/17 → 2015/16
Accuracy	GP+RL+RT+RP+RE+SE	0.9186	0.9175
	GP+PE	0.9065	0.8953
	PE	0.8554	0.9194
Sensibility	GP+RL+RT+RP+RE+SE	0.9676	0.9722
	GP+PE	0.9627	0.9513
	PE	0.9962	0.9999
Precision	GP+RL+RT+RP+RE+SE	0.8983	0.8936
	GP+PE	0.8844	0.8774
	PE	0.7521	0.8739

at the end of February, March, April and May. It is important to highlight that although the schedule of the course was similar in both editions, there were small differences between one academic year and the following one. Notably, despite these differences, the results are very good, even if some features (RT and RE in February; RE in March) did not were applicable yet by the time of applying the prediction model.

This is an indication that this prediction method can generalize well, and these students' data can be used by the teachers to predict (and avoid) learning failures, due to most of the features selected can be measured early in the course.

6 CONCLUSIONS

In this work we compare and combine the power of different statistical learning techniques for success/failure prediction in learning-oriented social networks. We select as predictors the factors or variables that have measurable correlation with the student's performance. The final results obtained are highly significant. In particular, our main conclusion

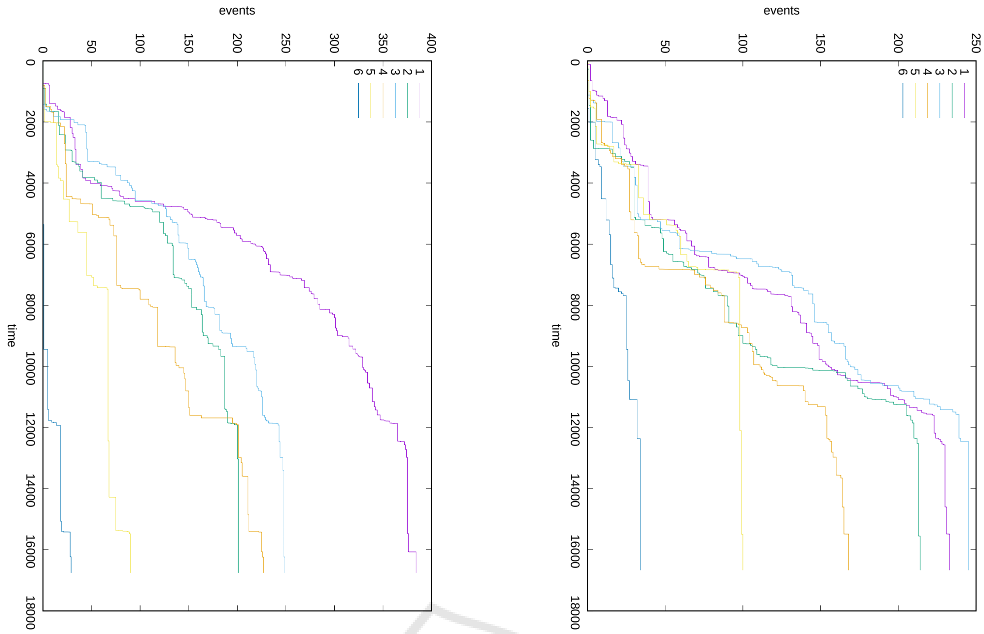

Figure 3: Accumulated events 2015/2016 (left) and 2016/2017 (right). The legend means: (1) Best final grade and in the top-ten of the ranking; (2) Second best final grade; (3) Best student in the ranking, a second-taking student in both editions and passes the course; (4) Intermediate position in the ranking and passes the course; (5) Drops the online learning activities in the middle of the term and fails the course; (6) Very low activity along the whole term in the platform and fails the course.

is that, according to our data, it is not the type of event/activity initiated by the student what best predicts his/her final grade, but the slope of the events he/she was engaged in. In other words, we have found that the pace of activities done by the students matters, much more in statistical terms than the kind of learning activity. This is a strong hint that these data, that can be measured early and accurately in the course, can be used by the teachers to implement timely pedagogical interventions.

REFERENCES

Brinton, C. and Chiang, M. (2015). MOOC performance prediction via clickstream data and social learning networks. In *INFOCOM'15, IEEE Conference on Computer Communications*.

Cadima, R., Ojeda, J., and Monguet, J. (2012). Social networks and performance in distributed learning communities. *Educational Technology & Society*, 15(4):296–304.

Chung, K. and Paredes, W. (2015). Towards a social networks model for online learning & performance. *Educational Technology & Society*, 18(3):240–253.

Eid, M. and Al-Jabri, I. (2016). Social networking, knowledge sharing and student learning: The case of university students. *Computers & Education*, 99:14–27.

Elgg. http://elgg.org.

Han, J., Kamber, M., and Pei, J. (2012). *Data mining: Concepts and techniques*. Morgan Kaufmann.

Hart, J. (2011). *Social learning handbook*. Centre for Learning and Performance Technologies.

Hastle, T., Tibshirani, R., and Friedman, J. (2008). *The elements of statistical learning*. Springer.

Hommes, J., Rienties, B., Grave, W., Bos, G., Schuwirth, L., and Scherpbier, A. (2012). Visualising the invisible: A network approach to reveal the informal social side of student learning. *Advances in Health Sciences Education*, 17(5):743–757.

Laat, M., Lally, V., Lipponen, L., and Simons, R. J. (2007). Investigating patterns of interaction in networked learning and computer-supported collaborative learning: A role for social network analysis. *International Journal of Computer-Supported Collaborative Learning*, 2(1):87–103.

Lykourentzou, I., Giannoukos, I., Nikolopoulos, V., Mpardis, G., and Loumos, V. (2009). Dropout prediction in e-learning courses through the combination of machine learning techniques. *Computers & Education*, 53(3):950–965.

Macfadyen, L. and Dawson, S. (2010). Mining LMS data to develop an "early warning system" for educators: A proof of concept. *Computers & Education*, 54(2):588–599.

Skrypnyk, O., Joksimovic, S., Kovanovic, V., Gasevic, D., and Dawson, S. (2015). Roles of course facilitators, learners and technology in the flow of information of a cMOOC. *International Review of Research in Online and Distance Learning*, 16(3):743–757.

SocialWire. http://socialwire.es.

Sousa, E., López, J., and Fernández, M. (2017a). Characterizing social interactions in online social networks: The case of university students. In *CSEDU'17, Inter-*

national Conference on Computer Supported Education.

Sousa, M., López, J., Fernández, M., Rodríguez, M., and Herrería, S. (2016). An open-source platform for using gamification and social learning methodologies in engineering education: Design and experience. *Computer Applications in Engineering Education*, 24(5):813–826.

Sousa, M., López, J., Fernández, M., Rodríguez, M., and López, C. (2017b). Mining relationships in learning-oriented social networks. *Computer Applications in Engineering Education*, 25(5):769–784.

Vassileva, J. (2008). Toward social learning environments. *IEEE Transactions on Learning Technology*, 1(4):199–214.