Success of the Functionalities of a Learning Management System

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Abstract: The goal of this research is to define and implement indicators for a Learning Management System (LMS). In particular, we focus on estimating patterns on the utilization of the message system by defining two quantities: the specific utilization and popularity. The idea is to take into account the perspective of academic institution managers and the administrators of the LMS, for example to understand if a particular department fails at providing a useful LMS service, or in order to allocate the correct amount of resources. These indicators have been tested on the LMS employed by the "Università degli Studi di Milano-Bicocca" (Milan, Italy), and in general provided a picture of poor utilization of the message system, where the usage follows a pattern similar to the Zipf law. This feature, correlated with the principle of least effort, suggests that LMSs should join forces with existing social networking systems to create strong online learning communities.

1 INTRODUCTION

Learning analytics (LA) refers to a wide range of fields of research such as process mining, business intelligence, data processing, information retrieval, technology-enhanced learning, educational data mining and data visualization (Scheffel, 2015; Romero et al., 2007). LA makes use of indicators and tools to understand, control and predict (Moodlerooms, 2017) the processes related to the learning activities for institutions at different academic levels ranging from primary schools, high schools to universities, workplace, etc. LA tools are becoming more and more popular in the e-learning community because they are considered an added value for Learning Management Systems (LMSs) as they provide an insight of the user learning activities allowing to determine e.g. expert users, at-risk students, etc.(Avogadro et al., 2016b; Sclater et al., 2016). Learning is a dynamic activity that requires a constant monitoring, evaluation, and adaption to the requests and needs of the stakeholders to guarantee analysis of quality and ad-hoc outcomes (Lukarov et al., 2015). In the last years, LA had a strong role within the context of the flipped learning (FL) paradigm where a novel and emergent approach to imparting knowledge is proposed (Filiz and Kurt, 2015). The FL is considered an extension of the flipped classroom paradigm where a key role is assumed by the social features within the learning practice. This view extends learning beyond the formal boundaries of the classroom and provides a virtual learning environment always available (i.e., anywhere and anytime) for consultation and knowledge sharing with a strong impact on understanding the social dynamics among peers. Thus, the evolution of learning (Dalsgaard, 2006) is going toward the definition of a social learning management system (Social LMS) which allows to provide a "complete learning environment" that takes into account the social elements (e.g. collaborating, networking and information sharing capabilities) to improve the practices of learning. Within these platforms, the social aspects become central for all the activities. Once a group of learners establishes a social network, it is possible to study their participation with social network analysis (SNA) techniques which allow to uncover non trivial structures (Rabbany et al., 2011). The advantages which can stem from the utilization of a Social LMS are related with (but not limited to) providing an easier and more uniform academic experience with the help of peers. Currently most of the LMSs cannot be regarded as "social" ones because of limited implementations of social features, however most of them include messaging systems which can be considered as embryonic versions of social LMSs.

Our research activity is focused on analyzing the modules defined in a LMS that are related to the knowledge sharing among peers for having an in-

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sight of the communication within the platform. For this reason, we decided to study the utilization of the messaging system of the LMS presently in use at the Università degli Studi di Milano-Bicocca, Italy. This LMS is an instantiation of Moodle, version 3.1. In the literature, LA provides insights for students with an opportunity to take control of their own learning, gives them a better idea of their current performance in real-time and helps them to make informed decisions about what to study (Scheffel et al., 2014; Scheffel et al., 2015). In addition, LA is a useful tool for teachers who can have a general vision on how learners are studying, the success of their learning practices, etc. (Mödritscher et al., 2013; Ferguson, 2014). Our research considers LA with a different look, the goal is to monitor the several LMSs functionalities for managing the governance of academic institutions to check how learners and academic staff interact with the LMS. This analysis could improve the decisional process of the policies (both hardware and software) dedicated to the effort necessary to provide to the users a LMS of quality. In our vision, the quality refers to provide efficient and effective e-learning services with good performances of usability.

The methodology followed in this research is the following: we first defined quantities of interest based on the present literature on the subject. Following these needs, a mathematical implementation has been proposed. The formulae have been confronted with data, and the patterns have been modeled with parametric functions in order to summarize the most interesting features. To this aim, we defined two indicators: "specific utilization" and "popularity", respectively; they are aimed at analysing how widespread a specific functionality of a LMS is. In detail, *specific utilization* is an indicator aimed at verifying how many users accessed to the LMS activities in respect to the whole possible users, whereas popularity is an indicator aimed at analysing the real usage of the functionality referred to the e-learning community which really accessed it. For a better understanding of this last functionality we defined the *real utilization plot*, which helps in visualizing the distribution of the utilization among the users. By observing the *real utilization plot*, it became clear a similarity of the observed trends with power laws, and thus we fitted the data and compared it with the Zipf law. As previously described, we have applied these indicators to the analysis of the messaging system used in an instance of the Moodle LMS. The indicators showed that the present utilization of the message feature is far from being mature (although it is growing).

The paper is organized as follows. Section 3 defines the indicators aimed at analysing the utilization of generic LMS activities, with the objective to tune the policies of governance for better managing the e-learning platform. Section 3 presents a case study where the indicators have been applied to analyse the "message" activity for the Moodle platform used at the Università degli Studi di Milano-Bicocca, Italy. Finally, in Section 4 the conclusions are stated.

2 RELATED WORK

The social activity of the students and teachers on a LMS has already been addressed in the literature. In this section, we provide a brief report of those works and the differences or similarities with the present paper.

A well known suite of learning analytics based on MoodleRooms is XRay (Moodlerooms, 2017). The users of this analytic tool are administrators, teachers and students, and its own main features include many statistical tools to control the learning trend of a course and make predictions about the behavior of the students less administrators. At variance with the LA provided by the XRay dashboard, the research presented in this paper is more focused on the administrators point of view, and in detail on the analysis of the message activity. The intent is to understand if the students/teachers access to the message activity properly. The indicators here provided are not defined in the actual version of XRay. (Macfadyen and Dawson, 2010) study how to predict the failure or success of the students of five classes of an online course (26 students) based on the information which can be retrieved from a LMS (which includes the total number of sent and read messages by each single user). A sociogram based on the properties is established in order better understand the dynamics among the students. On top of this a logistic regression is utilized for predicting the success of the learners. In this respect the study is also aimed at helping the teachers to have an evidence of how students are learning; but at variance with our work it is focused on the single student rather than providing a global utilization view of the features of the LMS. In (Romero et al., 2007) it is provided a survey of the data mining techniques which could result useful for a LMSs. In particular, it is shown how to implement these techniques for the Moodle suite. In (Rabbany et al., 2011) it is presented an interesting work on the importance of social network analysis in order to understand the structures which are present within groups of students. As an application, they provide a tool aimed at establishing educational social networks based on the asynchronous interaction provided by forums. Also in this case the aim is not

to provide a tool to control the utilization of the message system but rather the structures arising within the students. (Avogadro et al., 2016a) provide an extended method to create social graphs due to the interaction for both synchronous (chat) and asynchronous (forums) social interactions within a Social LMS, moreover the time dependence of the bond between students is explicitly taken into account. As an experiment, a learning management system for two courses is replaced by the Facebook groups in the work by (Wang et al., 2010). Since Facebook is an extremely popular social tool, it becomes natural to try to understand if it can effectively replace a LMS. The result of the research is that the features of a carefully made LMS are still superior to the functionalities provided by Facebook moreover some students were concerned about their privacy.

3 INDICATORS OF UTILIZATION

Modern LMSs provide a large variety of functionalities/activities (such as, messaging system, chat room, forum, etc.), it is thus natural that some of them have higher or lower success in terms of access by the users. Users can be divided into two groups: students and academic personnel. Students refer to the learners who access to the LMS functionalities to acquiring new skills, sharing materials, etc.; whereas, academic personnel includes teachers, university managers and LMS administrators. The e-learning community is very heterogeneous, it is thus common for LMSs to be provided with monitoring systems which allow to control the activities from different points of view. For example, a student might be interested in his/her own grades, a teacher might be interested in the activity of the single student or a whole class within a single subject. This paper is focused on the point of view of the university managers and LMS administrators who are responsible of providing the services of the LMS. This research proposes an approach to help the governance of an academic institution, where the utilization indicators of a LMS are naturally divided according to different features/parameters (such as courses, academic years, etc.) that allow to correlate the utilization with the structure of the courses. The term utilization in the present paper is referred to the amount of accesses to a given LMS functionality. This quantity can be specifically divided according to particular needs, for example if a person is interested in understanding the structure of a university it is meaningful to divide the indicators into different "departments", and academic years. In this respect, we propose to consider the amount of accesses divided by the total number of possible users. This quantity has been called *specific utilization* (or, in short, *su*) and it is obtained with the formula:

$$su(a,t,\mathbf{p}) = \frac{\#\,of\ accesses(a,t,\mathbf{p})}{\#\,of\ users\ who\ can\ access(a,t)} \quad (1)$$

This quantity provides a direct insight of the diffusion of a specific LMS functionality among the users within a particular department/area/course of utilization (a), at a given time (t), according to one or more given parameters indicated here with the vector ($\mathbf{p}$). For example, in the following we will consider the message system accessed by students of the LMS in use at the Università degli Studi di Milano-Bicocca, where the parameter ($\mathbf{p}$) refers to the fact that we want to distinguish between the sent only or received only messages, and we are also interested in distinguishing subsets of the whole community who can access to the functionality. Clearly the *specific utilization* can be evaluated for other functionalities accessible to the students of a LMS. In practice, in order to calculate this quantity, it is necessary to know a timestamp, and an identifier of the student who accessed it. Binning the utilization within fixed time spans allows to set the time granularity of the information (the academic year is a very natural choice, but one can decide to follow shorter or longer time frames).

The *specific utilization* indicator provides a quick insight about the success of a functionality, however it is important to consider that some activities (although accessible to the whole student population) might be aimed specifically to a restricted group and, for this reason, it might be more interesting to obtain specific information about the utilization of those who really accessed to the functionality (while neglecting the information regarding those who could access to the functionality but for some reason did not do it). For example, a functionality relevant only for a small subset of the whole student population, might obtain a small *specific utilization* score, although it had reached most of the intended users. This is the case of the message system for the present case study (Moodle at Università degli studi di Milano-Bicocca) where all the enrolled students have access to it, but some departments have a very limited implementation of the platform and, as a result, it becomes essentially useless for the student to access message system.

In order to better understand the real usage of an activity, we consider a plot (called *real utilization plot*) where on the abscissa there is the total number of accesses to a given activity of the LMS, while on the ordinate we consider the amount of students which used the activity that particular number of times. A graph of this kind can return interesting information

about how the students interact with the functionality. If the majority of the population accesses the functionality for a very limited number of times one can expect that the functionality does not require many usages to provide a complete experience. As an example, one might consider the accesses to the area of the website containing the forms for the definition of the curricula. Since one student does not modify daily his/her own curriculum path, this functionality is expected to be subject to a limited number of accesses per student (but most of the students should access it). If the data utilization of this functionality shows that there is a large amount of students who accesses the curriculum web page tens of times, this might imply that the associated web page does not provide a clear indication of the meaning of the forms and this puzzles the students who need to access repeatedly before solving their problem. A completely different scenario would be related with the social functionality of a LMS which allows the students to share information with their peers. In this case, if the vast majority of the students accesses this functionality a limited number of times it is reasonable to think that a critical number of users has not yet been reached and for this reason the functionality is not really working as a social binding mechanism. From the *real utilization plot* as detailed above, it becomes natural to extract the weighed average of utilization, which we call *popularity*:

$$popularity(a,t,\mathbf{p}) = \frac{\sum_{n=1}^{\infty} n \cdot U_n(a,t,\mathbf{p})}{\sum_{n=1}^{\infty} U_n(a,t,\mathbf{p})}, \quad (2)$$

where the sum runs over the number of accesses n, which ranges from 1 to infinity (this is not a problem since U_n is different from 0 only on a finite number of values, which depends on the binning procedure), $U_n(a,t,\mathbf{p})$ is the number of users who accessed n times to the functionality according to the department (a), time (t) and (possibly) a set of features denoted as ($\mathbf{p}$). As a normalizing constant, we divide by the sum of the users which accessed the functionality). The *popularity* indicator provides a value of how much the feature is accessed by the real users (not counting those who could access and did not access).

From the point of view of the administrators of a social LMS the *popularity* of a given module provides a simple insight about the utilization of the module itself (once the number of users is known). Given the (average) amount of resources which are required for a single utilization times the *popularity* times the number of accessing users allows for an estimate of the total amount of resources required. Since this study is aimed in particular to universities it is natural to think that different departments might have different managements, and for this reason the *specific utilization* and *popularity* are expected to be a function of the department and the time span considered.

4 CASE STUDY: MESSAGE MODULE OF MOODLE

This research belongs to a broader project regarding learning analytics with a particular attention to Social LMSs. Social LMSs are not yet as diffused as the "normal" LMS. For this reason, we decided to understand the impact of the social features of a "normal" LMS to estimate their utilization. The data analysed in this study belongs to the implementation of Moodle in use at the Università degli Studi di Milano-Bicocca (the version currently employed is 3.1.3). Moodle is a very popular (over 70000 sites in 233 nations) Learning Management System based on the pedagogical principles of social constructivism, it is an open source project regulated under the GNU GPL licence which allows for the creation and management of online courses. By using MySQL and R we were able to obtain the relevant information and calculate the indicators described in the previous sections. There is a message module available for Moodle which allows a student to interact, and exchange knowledge related to the university or informal material. This module represents a step toward a social LMS and as such we wanted to understand its success in a medium-large state university like Università degli Studi di Milano-Bicocca where all the students (about 35000, per academic year during the years of our analysis) are granted access to this functionality (all the data of the rest of the paper refers to it).

4.1 Specific Utilization

This paragraph describes the application of the *specific utilization* indicator detailed in Section 3 for the academic years 2013/2014, 2014/2015 and 2015/2016. As detailed above, the idea is to use the indicators for a better governance and control of the university (both from the point of view of the administrators of a LMS and the teachers responsible for its utilization among the different departments). The process of retrieving the department of each student was rather cumbersome: from each message, we were able to obtain the internal email of the sender, at this point it was possible to find all the courses where the student was enrolled. In the database, each course is associated with a "department/area", and thus it was possible to link at least one department to each of the courses. Unfortunately, some of the courses were shared between different departments and this could

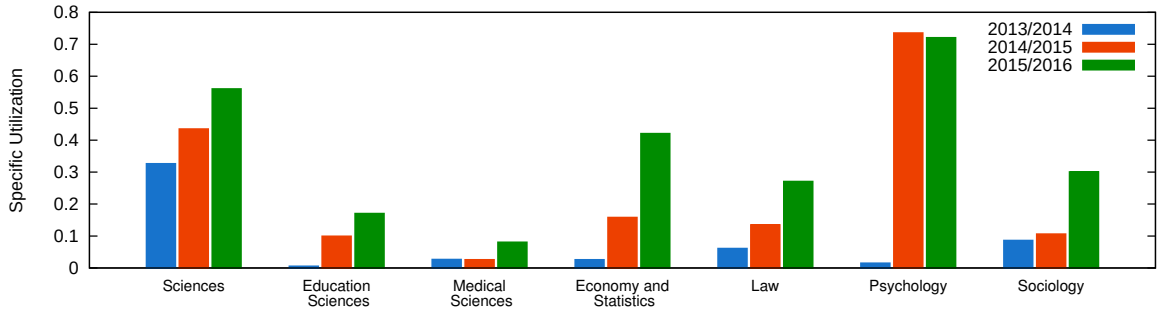

Figure 1: Specific Utilization of the sent messages among the students.

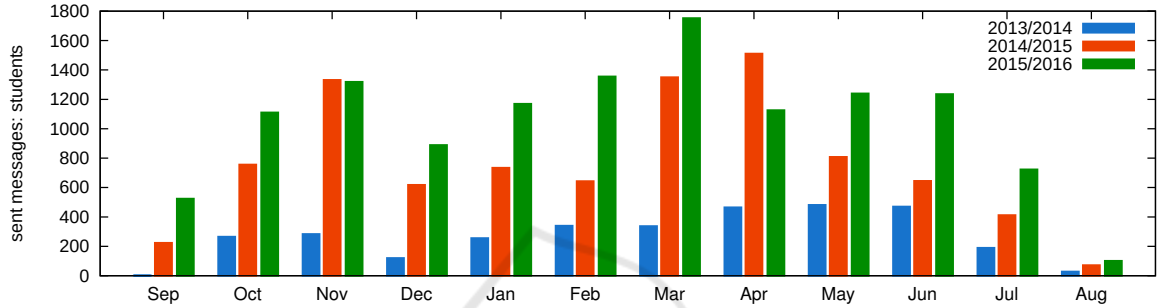

Figure 2: Total amount of messages sent by month in the three academic years.

lead to uncertainty, i.e. whether a student belonged to one or the other department. At present, this uncertainty cannot be avoided, and as a result some students have been classified in more than one department. Since this problem affects a minority of the population (less than 5%) we included in our analysis all the possible students for each department, allowing for duplicates. This implies that all the results presented in this

paper are subject to an error of the order of 5% in the quantification of the indicators. Because of the Moodle implementation, the act of sending or receiving messages provides different insights about the usage of the message functionality and for this reason a distinction should be made. In the formula presented in Section 3 we introduced a vector parameter **p**, for discriminating the functionality under investigation among different properties, in this case the parameter is a scalar, p which indicates whether we are considering only sent messages or only received messages (which can also be associated with different groups of senders/receivers). The reason for this discrimination is that the LMS of the Università degli Studi di Milano-Bicocca allows students to send messages among each other, but it also allows teachers and administrative employees to send messages. While the students can only send one-to-one messages (one sender and one receiver), the administrators and teachers can access to the modality one-to-many (one sender many receivers). This last feature is particularly useful when general information has to be sent to many people, nonetheless is seems clear that there is a difference in the purpose of the one-to-one and one-to-many messages. On the other hand, there is no explicit track on the system regarding whether the message was a one-to-one or one-to-many (a detailed analysis of the body of the message could overcome this problem but at the present stage of this work it is beyond our scope), while we can distinguish between sent and received messages. In the case of the *specific utilization* associated with the sent messages we take into account only those messages which were sent by the student population and remove those which are due to the academic staff/teachers. By using this division, we want to obtain an information regarding the success of the message system among the students as a socialization mean. In Figure 1 there is the *specific utilization* for different departments and during the academic years under consideration; it is interesting to notice that this indicator is higher in the Sciences and Psychology departments than in the Sociology or Medical ones (this last one attains the lowest score among the departments for the academic year 2015/2016). On one hand, there has been a noticeable increase in the utilization since 2013/2014.

However, the absolute values of the *specific utilization* in all the departments is very limited since it never exceeds 1.

This means that over one academic year, on av-

erage, each student used the message system to interact with another person belonging to the university less than one time. Similar figures can be obtained for the received messages but in this case the students received up to 3 messages per year (it should be noted that in this case the messages include also those sent by the academic personnel). The trend according to which the *specific utilization* increases is common among all the departments. For a better understanding, we decided to consider the total amount of sent messages on a month time frame, while we did not divide among the departments for a better readability (Figure 2). Only during April 2016 there has been a slight decrease in the total number of sent messages. The present values of the indicators, however, confirm a picture where the increase in utilization of the message modulus from the students, although noticeable, is not going toward important values within the next few years, for example the highest increase was in the Psychology department from 2013/2014 to 2014/2015 and it was less than 1 message per year. This increase can be attributed to internal regulations of the Psychology department, which underwent a change in the policies, according to which all the courses had to be available online on the Moodle framework (this was not true in the previous year). In this respect, this is an example of the impact that regulations can have on the utilization of a feature. However it also reminds that, when considering a social feature like a message system where the peers are expected to input and populate the data, a single policy does not necessarily have an impact which can provide qualitative change. The social network which should result from the exchange of messages suffers, in fact, from the very strong concurrence of other means of communication (Susilo, 2014) which are already well established among the students. In fact, even considering that all of the departments follow this increasing trend it would take tens of years to reach *specific utilization* values of the order of tens of messages per year. For this reason, the present status of the message system seems to require a qualitative change related to the LMS in order to reach a critical level. The indicators can thus be useful to the administrators to understand if their efforts to improve the message system are being successful or not.
There is clear indication of seasonality (see Figure 2), however the data in our possession regards only three academic years, and a possible seasonality analysis should be confirmed in future investigations. In particular during July, August and September the amount of messages exchanged is lower than the other months (due to the summer breaks), while March and April are typical exam session months which spark the need to exchange information.

4.2 Popularity

We consider here the popularity associated with the sent messages. The sent messages have been split in two parts, those due only to the students and those messages sent by the academic personnel (including staff and teachers). However, there is no direct distinction between administrative staff and teachers.

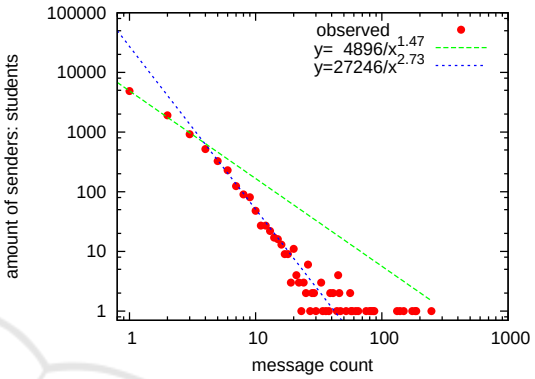

Figure 3: Real utilization plot of the sent messages for the students.

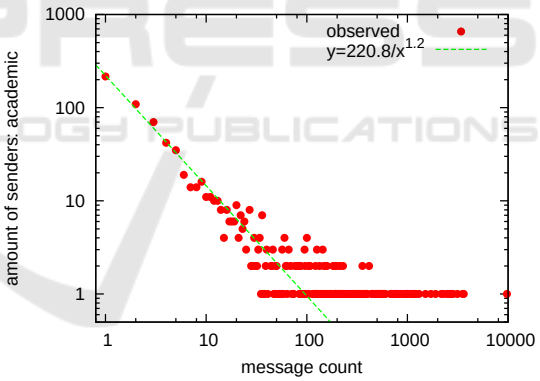

Figure 4: Real utilization plot of the sent messages for the academic personnel.

As a result, it becomes unfeasible to divide by department the senders labeled as academic. Since we were interested in comparing the functionality between the two user groups (students and academic), we did not divide by department the students either. The resulting graphs span many orders of magnitude in terms of number of users and of sent messages, as such we resorted at using double logarithmic plots for the representation (Figure 3 and 4). The total number of senders (students) in the academic years 2013/2014, 2014/2015 and 2015/2016 is 9330, and the number of sent messages amounts to 24881. As denoted in Section 4.1 the *specific utilization* of this

module is very limited. In Figure 3 it is shown the real utilization plot of the senders as a function of the number of messages sent during the three academic years. For a better understanding, we decided to use parametric functions to fit the data. A single parametrization does not seem sufficient to provide a comprehensive understanding of all the significant features. As a result, in order to constrain the functional behaviour we decided to fit it with two power laws of the form:

$$U_n = \frac{A}{n^k} \tag{3}$$

Where A is a constant, n represents the number of sent messages, while k involves the steepness of the power law (higher k implies a steeper descent as a function of n). There are at least three different patterns: between 1 and 4-5 sent messages the points seem to fit nicely a power law (which takes the form of a straight line in a double logarithmic plot), then there is a kink in the distribution, and the points between 5 and 20 messages form another line with a different slope (k). Above 20 messages it becomes difficult to consider the data as following a simple parametrization, this is also due to the fact that it is nonsense to have a fractional number of senders and this in turn implies staggering distributions. In the first part of the graph the power law which better fits the data has a coefficient $k = 1.5$ and A is 4896. The value of the parameter A is, essentially, the number of users which sent just one message during the three academic years. Between $n = 5$ and $n = 20$ the data distribution can be fitted nicely with a power law with exponent $k = 2.73$ (which implies a rather steep descent of the distribution) and $A = 27246$ (this would be the amount of users sending just one message if all the points followed this parametrization). The tail of the distribution corresponds to single students who sent many more messages than the average, however this tail does not represent a high percentage of the whole volume of sent messages. The *popularity* of the message module among the students is 2.8, which means that even those who used the message feature had a very limited access to it. A different situation arises when considering the diffusion of the message module among the academic personnel (staff and teachers). In this case, there are 531 active users who sent 73357 messages during the three academic years under consideration. The *popularity* of the message system among the academic personnel is 138. This shows that the message modulus is much more utilized by the academic personnel in respect to the students (although in this case the tail plays an important role). The data distribution (see Figure 4) seems to be reasonably explainable with a single power law

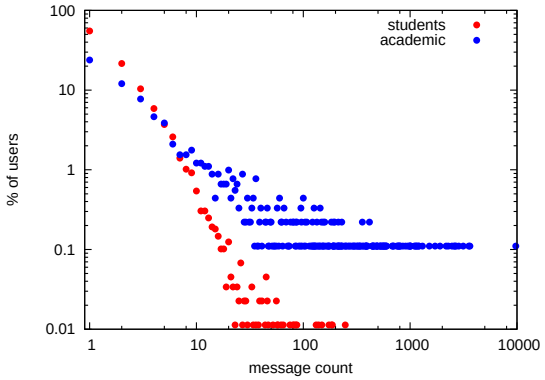

Figure 5: The percentage of message senders as a function of the number of sent messages.

from $n = 1$ to $n \approx 40$, where the exponent is equal to 1.2. Beyond n $\approx$ 40 it becomes difficult to use a parametrization since there are many single users who sent a lot of messages. It is useful to remind that the academic personnel can access to the one-to-many message system. For this reason, the users of the tail might appear as very active users, while in practice they are mainly sending the notifications to large groups of people at the same time.

We decided to compare the data obtained from the academic personnel and the students to better understand the different behaviours. However, the absolute values of the two cases differ by orders of magnitude and for this reason, in order to show both of the distributions on a single plot, we re-normalized the amount of users dividing by the total number of users who accessed to the message module (times 100, thus obtaining a percentage value). In Figure 5 the two different kinds of utilization are displayed. The usage due to the students shows shorter tails than the academic counterpart and also the number of users drops more quickly as a function of the number of sent messages. It is interesting to notice that around 20% of the academic personnel who accessed the message system did it only once, while this quantity raises to about 45% in the case of the students (this seems a clear indication of the fact that the academic personnel is more involved in the message system of the LMS). A confrontation of the shapes of tails is misleading. In the tails, there are single users who sent many messages but when re-normalized on the total population this returns different percentage values. Nonetheless it is striking that a large percentage of the population of the personnel belongs to the tails while the numbers are much smaller for the student population.

4.3 Zipf Law

Although the context is rather different, the utilization data here reported has some similarities with the Zipf law (Zipf, 1935). In detail, this law was first discovered studying the appearance frequency of words within a given text; the interesting feature is that (for a large set of texts, independent of the language or the nature of the text) the second most frequent term has a frequency which is roughly half in respect to the first one, the third most frequent word has a frequency which is about one third of the first one, and so on. The frequency of the n^{th} is thus $1/n$ in respect to the most frequent term. A generalized version of this distribution follows a law of the kind $1/n^k$, where patterns with k close to 1 are closer to the original Zipf law. The data collected from the messages sent by the students does not conform very well with the Zipf law (for example because a single power law does not provide a good fit of the data, Figure 3). Regarding the academic personnel however, the similarity between the classic Zipf law and the data collected is more interesting since a single power law with $k = 1.2$ provides a good explanation of the amount of sent messages (Figure 4). The Zipf law has been associated with the principle of least effort (Kingsley, 1946), according to which humans tend to use the least effort if the result is acceptable for a given purpose. In this respect since there are easier means of communication it is reasonable that the students resorted at using the message module only when other forms were not feasible. The academic personnel, however, which does not have the same level of personal connection with the students was simplified by the features accessible via Moodle. This could be confirmed by the long tails, where, for the teachers/personnel, becomes easier to send one-to-many messages through the LMS rather than via normal email where they should input the name of each receiver.

In considering the pattern displayed as due to the principle of least effort one can use this as a hint of success or failure of the message system. In a successful message system (e.g. Facebook chat, Whatsapp, etc.) the users are not aimed at doing the minimum possible effort to exchange information, while rather the information is naturally spread and enriched when passing from one person to the other. It is thus conceivable that the real utilization plot of a successful message system does not follow a Zipf-kind law, or at least that the exponent, associated with the descent in number of messages sent per person, should be very small (< 1).

5 CONCLUSIONS

In this research, we built indicators aimed at providing an analysis of the amount of accesses to the functionalities of a LMS. The goal is to provide tools which follow the perspective of the managers/teachers of the university; in detail, *specific utilization* provides information about the usage of a functionality in respect to all the possible users, while *popularity* provides insights about the real usage of those who actually access the functionality. These indicators have been tested on the database produced by an instance of Moodle 3.1, adopted by the Università degli Studi di Milano-Bicocca, Italy. As a result, it was possible to observe that the functionality under investigation, the messaging system, has not yet reached a critical stage where there are strong active groups creating a self-sustained community. The level of interest for the message system depends on the department but on the overall the utilization is very scarce. It has to be noted that there has been an increase of utilization through the years, however a change of paradigm is required in order to achieve an active social community. Although most of the students have never accessed the message functionality there is minority of them which did it. Even for those students the access was very sporadic, since the overall *popularity* is less than 3. A different scenario arises when considering the real utilization plot of the message system associated with the academic personnel. In this case the *popularity* reaches a value of 137 (although this is strongly influenced by the one-to-many message feature available to this group of users). The present analysis has been introduced to the administrators, and it is going to be taken into account for the next versions of the LMS. In the future, we plan to design more indicators in order to obtain a global monitoring of the functionalities of a LMS, and apply it to the case of the Università degli Studi di Milano-Bicocca.

The utilization indicators detailed for the message system can be implemented, in fact, for other kinds of modules of a LMS, and form part of a more general project aimed at providing tools to control and improve the learning experience both from the point of view of the students and the academic staff. A natural improvement regarding the social aspects of the message system is to monitor the timings between the act of sending and receiving a message, and to check for significant differences between these indicators due to the gender of the users.

An interesting outcome of this research is that the distribution of the users versus the number of sent messages for the academic personnel (*real utilization*

plot) follows quite well the empirical Zipf law. This is also true for the case of the students (although the parameters used to fit the data differ). The fact that these data follows power laws, might be interpreted as a sign that the users are employing the message system mainly when they are forced to do it (principle of least effort) rather than considering it as an everyday tool to be naturally used. The strong concurrence of popular messaging systems might be a cause of this unwillingness to use a more cumbersome module of a LMS and might suggest that a synergy with those systems (e.g. integrating the LMS and an already existing social network) might lead to better results in terms of establishing a strong social learning community.

This hybrid approach might help in overcoming some of the natural limits of the social communities which are being established on a LMS. First of all, the time window which is naturally bounded to the study course could be overcome (and for example the messages would not be "lost" after the person is no longer part of the LMS system). The students would not need to access to many different messaging system, and since they already access often times their favorite social network they would be updated in real time.

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