Using computer lab trace analytics to support learners' engagement in laboratory activities

L'analisi dei tracciati dell'uso dei computer per supportare il coinvolgimento degli studenti nelle attività di laboratorio

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ABSTRACT Laboratory based learning activities constitute an important part of students' learning experiences today. As a consequence, it is interesting to investigate how to better support such activities using digital technologies. In this paper, the authors present a practical approach based on the use of Microsoft Families and artificial neural networks to analyse computer traces of students' lab activities to identify students encountering difficulties and at risk of failure, and flag tutors for further corrective actions on demand. This work demonstrates how artificial neural networks allow the analysis of the traces of students' work even outside of a Learning Management System and with no clue of possible algorithmic relationships between the traces and the students' performance.

KEYWORDS Recommender Systems; Decision Support Systems; Learning Analytics (LA); Educational Data Mining.

SOMMARIO La attività laboratoriali costituiscono oggi una parte significativa delle esperienze didattiche degli studenti. Di conseguenza, è interessante osservare come poter meglio supportare tali attività usando le tecnologie digitali. In questo articolo, gli autori presentano un approccio basato sulle Famiglie Microsoft e sulle reti neurali artificiali che consente di analizzare i tracciati dell'uso dei computer nel laboratorio per identificare gli studenti in difficoltà e allertare docenti e tutor per attuare eventuali azioni correttive. Questo lavoro dimostra come le reti neurali artificiali consentano l'analisi delle attività degli studenti anche al di fuori di un Learning Management System e senza aver alcuna cognizione di relazioni algoritmiche tra tali tracciati e le possibili future performance.

PAROLE CHIAVE Recommender Systems; Sistemi di Supporto alle Decisioni; Learning Analytics (LA); Educational Data Mining.

1. INTRODUCTION

As stated in Brown (2011), we live in an increasingly digital era, characterised by information abundance and growing complexity. ICT technologies may be used for interacting with our family and friends, purchasing products, making travel reservations, filing income tax returns, learning, and so on. As individuals conduct these activities, they leave their "digital footprints" or "digital bread crumbs". These clues capture every detail regarding the user's interaction with any embedded enterprise-interface system such as time, location, keywords, search results, content created and consumed in the digital environment. In particular, as claimed by Chatti, Dyckhoff, Schroeder, and Thüs (2012), these "digital footprints" may be related to learning experiences and may be analysed to determine patterns and make predictions that can answer questions like: Which course is the most popular? Who are the students not performing well?

Despite analytics being common, many questions about them are still unanswered and opportunities exist for improved and refined analytics. In learning contexts, students leave a trace of what they do that reveals the strategies they adopt to reach a goal, the learning needs they have, their collaboration patterns with peers, their interactions with tutors and teachers. All of these aspects represent a wealth of knowledge that is usually recorded in final reports and, much more rarely, used to support on-going actions with the aim of improving individual or global learning performance (Persico & Pozzi, 2015).

Although there are many approaches that use traces in order to adapt and personalize the experience of users (Sah & Hall, 2009), few of them, in particular in the learning domain, are able to intervene "before it is too late", by showing tutors and teachers a forecast of the possible final results of a learning experience and giving them alerts when the processes their students are engaging in may lead them to a negative evaluation. This paper describes some experiments on how educational data mining based on neural networks may represent a possible way to support teachers and tutors in monitoring the activities of their students in a laboratory. For example, it could raise alerts suggesting when to intervene to prevent students from failures, thus leading them to better results and, ultimately, better evaluations.

2. RELATED WORKS

Educational data mining focuses on developing new tools and algorithms allowing systems to recognize data patterns concerning interactions between a student and an educational system. Particular data patterns coming from users' learning experiences have relevance because they may reveal how a student reached a result, the process followed, the engagement, etc.

Analytics is a relatively new field aiming to develop data analysis techniques widely used in a number of fields. As highlighted by Cooper (2012), some areas of application are statistics, business intelligence, web analytics and operational research. The use of analytics approaches in the context of learning processes is called *Learning Analytics* (LA). According to Siemens and Baker (2012), a widely accepted definition of LA was provided in the call for papers of the 2011 International Conference on Learning Analytics and Knowledge, and described the field as «*the measurement, collection, analysis and reporting of data about learners and their contexts, for the purpose of understanding and optimizing learning and the environments in which it occurs*» (n.p.).

The rise of LA comes from the opportunity to observe and track the learners' activities through log files. Logged data describe who the students are, which activities they carried out and when, and sometimes how and where they worked. Such intensive data collection produces the so-called Big Data that makes possible extensive use of data analysis procedures (de-la-Fuente-Valentìn, Corbi, Crespo, & Burgos, 2015). Non-intrusive measurement and collection is difficult to achieve in the learning context. The most popular method is to capture web interactions in a Learning Management System, but the captured data may not be fully representative of the student activities, and so other monitoring methods are required (Pardo & Kloos, 2011). In fact, another important focus of these methods relates to analysis and reporting from data representations that are often complex and difficult to interpret.

Methods used in LA, just to mention a few, include social network analysis (a process of investigating social structures through the use of networks and graph theory), collaborative filtering (a technique used by recommender systems to make automatic predictions), clustering (a technique of grouping objects in sets called clusters whereby similar objects are positioned in the same cluster), artificial neural networks (biologically inspired computer programs designed to simulate the way in which the human brain processes information). LA attempts to discover the factors that affect learning in a certain context, so that instructors and learners can reflect on these factors and improve their experience. Tools can be viewed as decision support systems, where the decision is aimed at driving one's teaching/learning methods.

A reference model for LA was proposed by Chatti et al. (2012) and features four dimensions: What? (What kind of data does the system gather, manage, and use for the analysis?); Who? (Who is targeted by the analysis?); Why? (Why does the system analyse the collected data?); and How? (How does the system perform analysis of the collected data?). These are the same dimensions adopted by Atif, Richards, Bilgin, and Marrone (2013). Lal (2016) reports an attempt to understand how to use LA to analyse the data and correlate them to student engagement. Educational institutes can utilize the intelligence revealed by LA processes for application in strategic institutional planning. As stated by Gaeta, Marzano, Miranda and Sandkuhl (2017), online learners continually leave behind digital footprints in their virtual learning environments, particularly with the increasing adoption of course/learning management systems (LMS). At its most basic level, LA involves using a web analytics program to track student activity on the LMS and their use of digital learning objects, as one way to gauge learner engagement (Sampson, 2016). These analytics systems are built into most LMS. Educators can use them to make real-time decisions on how they might modify their course to better suit learners, and to identify potential "at-risk" students who may need an intervention in order to avoid their failing a course module or an entire course (Sergis & Sampson, 2017).

In this paper, the authors address a different type of situation, because the context of the study is one where students do not work in a LMS, but rather in a real laboratory. They have common learning objectives and work in teams. The only instruments students have at their disposal are the computers connected to the Internet and some software application installed on them. So, what the authors can analyse is not the recording of student activities in an LMS, but the use they make of computers during lab sessions: the time they spent, the software they used, the Internet searches they did, the keywords they used, the completed artefacts and so on. Therefore, the relationship between these traces and the activities carried out by the students is less direct than the traces left in an LMS. However, the underlying hypothesis of this work is that the traces of PC use in the computer lab during the group activities may be indicative of the overall result of the work done by the students involved.

The aim of this paper is to test this hypothesis in the experimental setting described below and, specifically, to understand if neural networks can be used to this end. The rationale for the choice of neural networks is that they can help find correlations among data when no rules or specific knowledge can be applied. Their effectiveness increases with the amount of data available. The term "neural network" has its origins in attempts to find mathematical representations of information processing in biological systems. Methods based on neural networks very broadly cover a wide range of practical applications of pattern recognition (Bishop, 2006).

3. AIMS AND METHOD

The aim of the paper is to test the above hypothesis by using basic technological tools to make a preliminary analysis aimed to understand when to intervene to correct student paths, especially to tackle declines in students' attention during laboratory activities, thereby improving the level of their engagement. If this approach works with simple technology, the authors could then extend it in "smart" environments in which the presence of other sensors may offer more accurate information and thus give greater powers to intervene. In their computer lab, the authors have been monitoring the use of each PC by means of *Microsoft Families* (Trent, 2015), a system designed to allow parents to monitor their children's actions' on the PC. *Microsoft Families* keeps track of the time spent, applications used, websites visited during web browsing, and keywords adopted in web searches.

The experiment involved the definition of a task to be assigned to the working groups and the availability of a panel of experts to judge the results of the work performed. To this end, a team of teachers was recruited. They assigned the task to each working group (consisting in building a knowledge map and producing a slide-based presentation) and defined the criteria for evaluation of the produced artefacts. The criteria they adopted are based on the following indicators (Marzano & Vegliante, 2017):

- evaluation of the knowledge map (concept descriptions, relations, hierarchies, instances);
- evaluation of the presentation (formal quality, content quality, technical requirements in terms of balancing text, images and audio, scheme effectiveness, text clarity, durations).

The available data set consisted in the traces recorded by *Microsoft Families* week by week, the workgroup products, and the evaluation given by the panel of experts. Short of rough errors of assessment, the researchers believe the judgment of the produced evidence is indicative of the preparation, work method and level of involvement of the students in their group. Thus, the authors sought to apply data mining techniques on the tracked data to analyse the paths of the workgroups and compare these with the expert evaluations they received in order to identify specific patterns or significant behavioural signals. The authors think data mining may provide the basis for developing a system able to detect the situation in which the working group finds itself, to monitor the process underway, to estimate the level of involvement of group members and, consequently, to activate appropriate actions to alert groups or provide them with guidance and suggestions. Of course, the authors do not know any *a priori* rules to apply for understanding or classifying the behaviours of the workgroups. In a first step, the authors may label a behaviour according to the judgement of the panel of experts.

Since the work of a group of students in the lab is carried out using a number of computers at a time (up to 10 PCs), the picture to observe consists of a massive array of data that include times, applications, visited websites and keywords of all the computers used during the various group sessions. Our idea is to develop a soft computing system that learns the correspondences between this observed picture and the related final evaluation so that the researchers can employ the system to observe new pictures and estimate a possible evaluation for them by recognising the situations the students are experiencing, those that lead to positive results and those that lead to negative results. This makes it possible to achieve an important educational objective: a system that supports teachers and tutors in taking actions in progress. If they encounter a positive situation, they may encourage the students involved; conversely, if they encounter a negative situation or a situation "at risk", they may try to intervene by providing suggestions to the students involved and implementing remedial actions "before it is too late".

4. EXPERIMENT SETTING

The experiment was carried out during two different academic years: 2016/17 and 2017/18 with 56 workgroups, each comprising three to six students. The total number of students engaged was more than 300 (113 in 2016/17 and 203 in 2017/18). They were enrolled in the bachelor's degree course in Primary Education Sciences at the University of Salerno, attending the course "Didactics and didactic technologies".

The experiment setting was the university's Rimedi@ Lab (Figure 1), equipped with 28 PCs running Windows 10 and each with a Microsoft account. The authors created a *Microsoft Family* for the lab, where an account is the *parent* and all the other accounts are the *children*.

The learning tasks assigned to the working groups were (1) creating multimedia presentations to use with students on disciplinary matters (e.g. mathematics, science, grammar) and (2) producing concept maps using specific bibliographic materials (essays, articles in Italian and English) and open-source software (in particular, *Freemind*).

The researchers followed each group accessing the Rimedi@ Lab for eight working sessions distributed over four weeks, and they collected all the recorded tracks as the dataset. After four weeks of work, a board of teachers and researchers evaluated all the material produced by each of the workgroups. The students had been able to use the computers to perform web searches, visit websites, open and use the available applications to write texts, create sheets or presentations, etc. Since the students were all together in the lab, they were also able to work together on the same computer. The researchers did not keep track of these aggregations, even though they had a web camera available for future use; for these experiments, they only used the traces and the dataset described in the previous section.

Figure 1. The Rimedi@ Lab.

The Microsoft Family tools were used to monitor and record the behaviour of the students, as parents would with their children. Microsoft Family tracked what each workgroup did in the laboratory during the experiment: when the PC was used (days of the week and time for each day), apps used and time for each app, websites and visits for each site, keywords searched. Table 1 shows an example in detail.

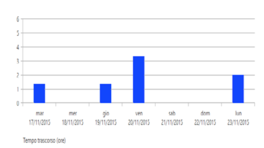
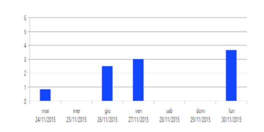
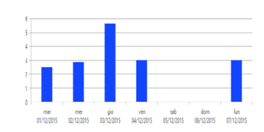
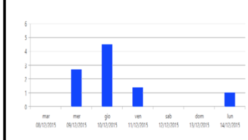
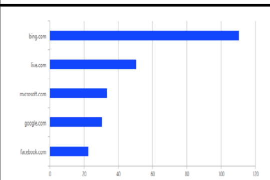
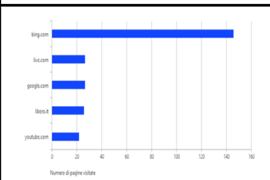
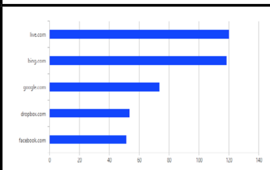
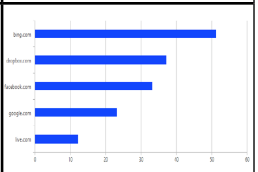
	Week 1	Week 2	Week 3	Week 4
Days and time for each day				
Apps and time for each app	Microsoft Edge 5 hours and 57 minutes Microsoft PowerPoint 3 hours and 8 minutes Java Runtime (javaw.exe) 1 hour and 6 minutes Microsoft Word 38 minutes SMART Board Tools 8 minutes	Microsoft PowerPoint 5 hours and 13 minutes Microsoft Edge 4 hours and 54 minutes Microsoft Word 1 hour and 34 minutes Java Runtime (javaw.exe) 58 minutes Microsoft Paint 11 minutes	Microsoft PowerPoint 11 hours and 36 minutes Microsoft Edge 5 hours and 24 minutes Java Runtime (javaw.exe) 4 hours and 33 minutes SMART Board Tools 45 minutes Microsoft Word 24 minutes	Microsoft PowerPoint 8 hours and 16 minutes Microsoft Edge 1 hour and 45 minutes Firefox 1 hour and 7 minutes Microsoft Word 47 minutes Java Runtime (javaw.exe) 29 minutes
Websites and visits for each site				
Keywords used for searching	homo sapiens sapiens multimedia per bambini homo sapiens sapiens homo sapiens sapiens mappa concettuale di cosa si nutriva l'aspropoliteco caratteristiche principali austropoliteco…	bambini cartoni animati animale cartone animato rino amico scienziato bosco con gnomi disegno per bambini bosco per bambini immagine bosco imagine libero mail…	filastrocche sulle vitamine per bambini libero mail gif animate sumeri gif animate scuola elementare gif animate sumeri gif sui sumeri…	Magisto il ballo dei segnali mammut era glaciale cro magnon per bambini cavernicolo immagine animate GIF ANIMATE uomo caverne caverne pittura …

Table 1. The recorded track for one PC over four weeks.

5. DATA COLLECTION AND ANALYSIS

The researchers collected a track like the one exemplified in Table 1 for each one of the computers used in the lab, together with the multimedia presentations produced by the groups and the evaluations they received (Figure 2). Adopting an approach similar to those adopted in Miranda and Ritrovato (2015), the authors codified all the data using simple vocabularies.

The results of each workgroup were codified using three labels (poor, intermediate, good) represented as three different sequences of bits: {1, 0, 0} for poor, {0, 1, 0} for intermediate and {0, 0, 1} for good. Thus, in order to create a dataset, they considered the codified tracks of the computers as possible input and the codified evaluation as related desired output.

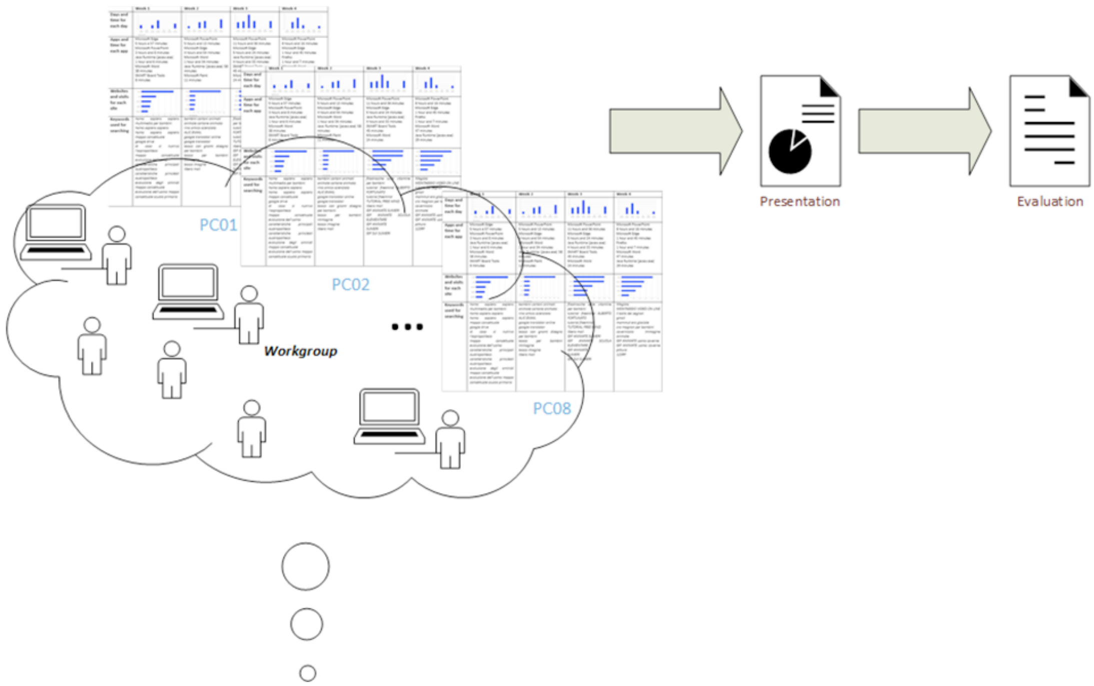


Figure 2. The collected data for each workgroup.

For instance, a pattern of a well accomplished piece of work has about 400 input data codifying the computer use as a sequence of numbers {17, 18, 11, 179, 257, …} and three outputs codifying the good evaluation as {0, 0, 1}. In the same way, a pattern of a poor work has a different sequence of 400 numbers as input and three outputs codifying the poor evaluation as {1, 0, 0}.

A first step of statistical analysis did not reveal any statistical or logical correlation among inputs and related outputs in the created dataset. The researchers then decided to adopt a neural network approach and sought to train it on this dataset in order to understand whether there are possible relationships.

In a first attempt, as showed in Figure 3, the authors trained a neural network on the created dataset by getting the data from all the four weeks as input and the codified evaluation as desired output. This dataset is the training set for their network.

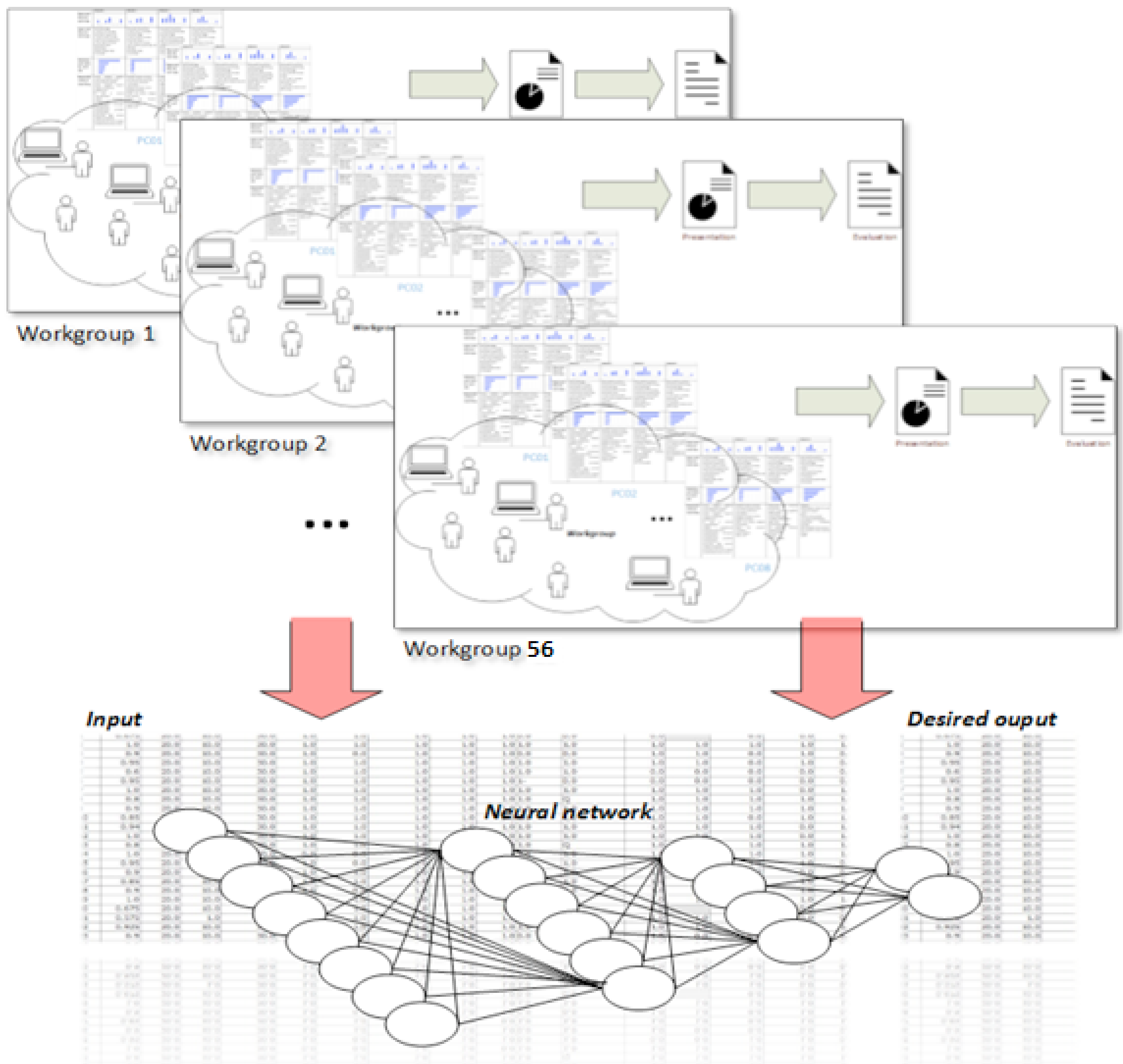


Figure 3. A first attempt at training a neural network on the data generated over four weeks by 56 working groups.

Applying the same neural network simulator used by Barile and colleagues. (1999), the authors defined a neural structure with about 400 inputs and 3 outputs, in accordance with the training set (TS). As suggested by Bishop (2006), the authors split the TS in two parts, one for the training and the other one for the testing. Applying a training algorithm, the authors trained the network on only the first part and evaluated its effectiveness in classifying patterns by getting its outputs on the other patterns coming from the second part (the testing set). After this training process, the neural network showed less than 2% of maximum error on the patterns of the training set and less than 8% on the patterns of the testing set (Figure 4).

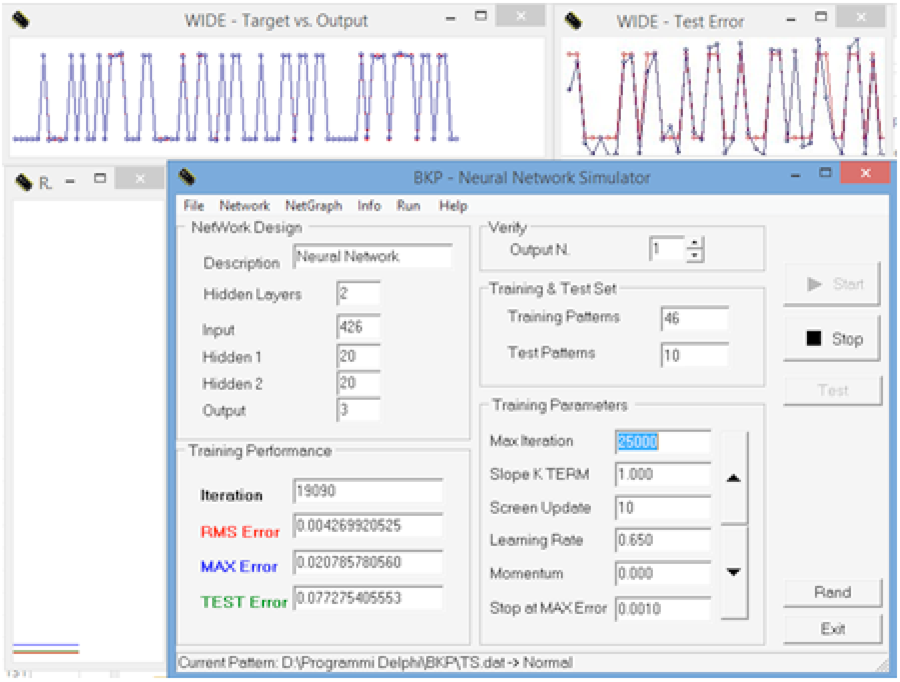


Figure 4. The neural network trained on the first attempt:
56 patterns, each with 426 inputs and 3 outputs.

Thus, the authors can assert that the classifier is ready to use. It can now be adopted to estimate the quality of the work done by the working groups: for new workgroups, the tutors get the tracks and, using the trained neural network, they are able to forecast the performance of students and, subsequently, the evaluation they will probably receive.

In a second attempt, the researchers sought to do the same using only the data from the first two weeks of work (Figure 5). This means a considerable reduction in input (only half the amount of data is considered), which is very important for possible on-the-fly application. Indeed, it should make it possible to estimate the result by taking into account only two weeks of work, giving teachers and tutors enough time to send feedback and suggestions, and modify the working path followed by the workgroup accordingly.

As in the previous attempt, the authors defined a neural structure, this time with 213 inputs and 3 outputs, in accordance with the training set (TS). The number of patterns and the partition between training set and testing set remained the same as in the previous attempt. Applying the same training algorithm, the authors made a neural network with less than 8% maximum error on the patterns used and less than 13% on the patterns of the testing set. This second network is now ready to be used as a classifier and, thus, as a tool to forecast the performance of a working group (and the possible evaluation it will receive) by analysing its two first weeks of work done.

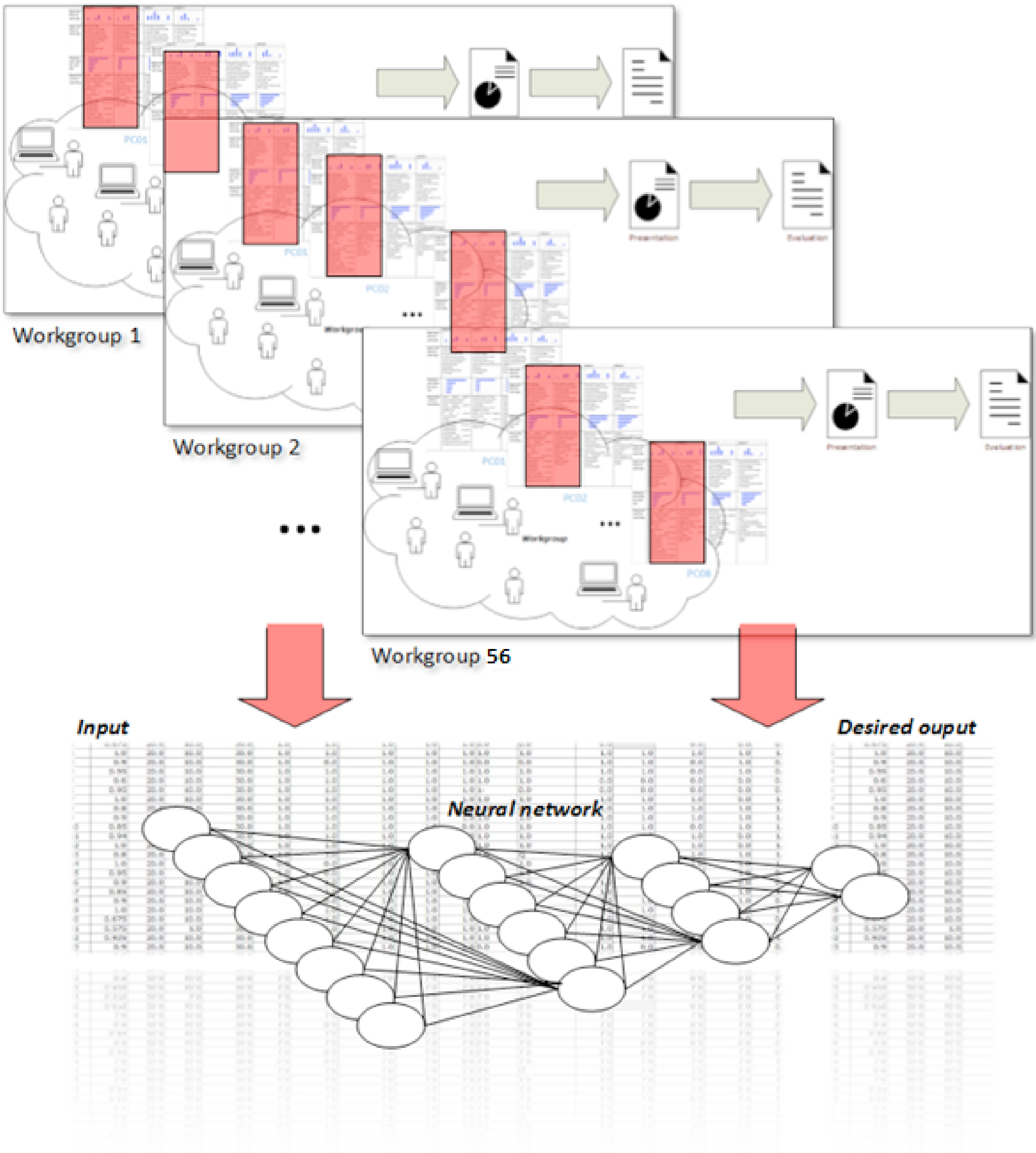


Figure 5. The second attempt: a neural network trained on the data generated in 2 weeks by 56 working groups: 56 patterns, each with 213 inputs and 3 outputs.

6. DISCUSSION

The researchers gathered the dataset using the *Microsoft Family* traces related to the work done by groups on their computers during the four-week experiment. Each track may be a significant representation of the behaviour of each workgroup since it takes into account only simple quantitative data: it includes what the students actually did on the PCs. Moreover, the authors also gathered a qualitative evaluation of the work done by the workgroups. By putting together these data, the authors constructed the dataset and used it as a

training set for two neural network prototypes.
By applying a training algorithm, they were able to classify the behaviours of the groups. Thus, the network prototypes seem to be able to forecast the possible evaluation the groups will receive on the work they have performed. The first attempt was intended solely to demonstrate the described approach, while significant results were gained from the second attempt. Subsequently, it is possible to assert that by adopting the proposed approach of analysing only two weeks of work, tutors and teachers may have a first forecasting of the final evaluation. This allows them to estimate the possible final result of their students while work is still in progress, rather than at the end of the learning experience This has the advantage of providing an opportunity to give students feedback, suggestions and information: this is useful to them for finding a satisfactory way to complete the work, to modify their adopted approach, to improve their engagement and, ultimately, to enrich the learning process.

7. CONCLUSIONS

Understanding the use of innovative environments in which learning takes place introduces a new challenge. Increasingly, students will be looking for support from LA outside the environment itself, since they are engaged in lifelong learning in open, informal or blended environments. This will require a shift of researchers' attention to a number of different datasets that are not strictly related to the learning process, such as data from learners' mobile devices, biometric sensors and data related to mood and the different manners in which these may be combined.
The authors of this paper began with preliminary experiments on the dataset from the logs of the computers used by a set of workgroups, and this allowed them to forecast student performance and evaluation of the produced works. The researchers have implemented their idea by developing and training neural networks on the created datasets. This has allowed them to produce a data mining system able to identify the situation a workgroup is experiencing when pursuing a given learning objective. The system takes as input two weeks of logs from the computers used by the students in the workgroups and is able to forecast the performance of the workgroup and the evaluation of its final product. The positive results of this early experimentation have led the researchers to believe that the implemented system may really be a prototype of a support system for teachers and tutors in monitoring students' lab experiences, supervising their activities in workgroups and generating alerts related to the situations the groups are experiencing. This yields understanding about where each workgroup is and what feedback the tutors should send them to improve the activated processes and related results (Scriven, 1967) and to promote self-assessment and self-regulation (Brookhart, 2013; Weurlander, Söderberg, Scheja, Hult, & Wernerson, 2012).
The researchers are confident they can extend this approach to "smart" contexts, where the logs of computer use may be supplemented by other kinds of data and information coming from other sensors and observations. It may also be possible to perform a semantic injection to interpret the gathered data in order to improve the accuracy of the system and to give teachers and tutors the possibility to intervene more effectively.

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