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Doctor, F. and Iqbal, R.

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# An Intelligent Framework for Monitoring Student Performance Using Fuzzy Rule-Based Linguistic Summarisation

Faiyaz Doctor *Member IEEE*, Rahat Iqbal  
Intelligent Information Modelling and Retrieval Group  
Faculty of Engineering and Computing  
Coventry University  
Coventry, UK  
Email: faiyaz.doctor@coventry.ac.uk

**Abstract**—Monitoring students’ activity and performance is vital to enable educators to provide effective teaching and learning in order to better engage students with the subject and improve their understanding of the material being taught. We describe the use of a fuzzy Linguistic Summarisation (LS) technique for extracting linguistically interpretable scaled fuzzy weighted rules from student data describing prominent relationships between activity / engagement characteristics and achieved performance. We propose an intelligent framework for monitoring individual or group performance during activity and problem based learning tasks. The system can be used to more effectively evaluate new teaching approaches and methodologies, identify weaknesses and provide more personalised feedback on learner’s progress. We present a case study and initial experiments in which we apply the fuzzy LS technique for analysing the effectiveness of using a Group Performance Model (GPM) to deploy Activity Led Learning (ALL) in a Master-level module. Results show that the fuzzy weighted rules can identify useful relationships between student engagement and performance providing a mechanism allowing educators to transparently evaluate teaching and factors effecting student performance, which can be incorporated as part of an automated intelligent analysis and feedback system.

**Keywords**—student performance monitoring; fuzzy systems; linguistic summarisation; activity led learning

## I. INTRODUCTION

Over recent years there has been an increased interest in engaging students more directly in their learning [3] [15]. It is well known that students learn better if they are involved in practical and independent activities. Educators have adopted a variety of pedagogical methodologies including Problem-Based Learning [10] Enquiry-Based Learning [11] and Activity-Led Learning [31] to provide students with opportunities to work on specific practical tasks. The development of Technology Enhanced Learning (TEL) allows the interplay between learning activities and respective technologies such as software for content delivery, activity management and self-directed learning. These technologies provide a means by which educators can

more efficiently deliver teaching material, set activities and assess individual and student groups on learning tasks.

In order to assess students’ progress on learning tasks it is necessary to capture data about the underlying characteristics of learners; engagement, behaviour and performance on learning tasks. These activity characteristic can comprise of time spent on tasks, level of prior knowledge, attention on learning activity (through mouse clicks and focus changes events), online / in-class quizzes and interim test scores. These can be elicited from electronically submitted exercises, activity reports, and online questionnaires and computer based software plug-ins, which are integrated as part of the TEL systems.

The extracted raw data on its own is not understandable and requires educators to perform the time consuming task of having to interpret and analyse it manually using a variety of different statistical approaches to identify patterns of characteristics effecting students performance. This is not effective for supporting more continuous monitoring and analysis of progress. The raw data would also contain a mix of numerical and categorical parameters, where numerical parameters would contain uncertainties related to how the recorded values are associated with performance related outcomes in the data. It would therefore be useful to classify and summarised the data in order to extract useful patterns and associations for making informed decisions on students’ progress. It is important that the outputs of any such system are presented in a transparent and linguistically interpretable way to lecturers and teaching assistants, to help support their teaching decisions over the course of the activities.

The work described in this paper is a part of wider effort carried out at Coventry University towards the development of Activity-Led Learning (ALL) and automated student feedback based on intelligent analysis. The rest of the paper is organised as follows. Section II presents a literature review of data mining approaches applied to analysing student performance. Section III describes the fuzzy rule based Linguistic Summarisation (LS) technique that was applied. In Section IV we describe our proposed framework for monitoring student performance. Section V presents a case study and initial experimental results of applying the fuzzy LS approach to group performance analysis of students engaged in Computer Supported Collaborative Learning (CSCL) activities. Finally conclusions and future directions are presented in Section VI.

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F. Doctor, and R. Iqbal are with the Intelligent Information Modelling and Retrieval Group, Faculty of Engineering and Computing Coventry University, Priory Street Coventry, CV1 5FB, UK (e-mail: faiyaz.doctor@coventry.ac.uk).

## II. LITERATURE REVIEW

Data mining and knowledge discovery techniques can be used to automatically model or classify students to identify patterns of abilities, interactions, levels of interest and engagement that result in either good or poor performance. Techniques such as statistical classifiers, decision trees, rule induction and neural networks have been applied in [21] and [18] for classification and performance monitoring of students. In [23] an empirical approach that makes use of neuro-fuzzy synergism to evaluate the students in the context of an intelligent tutoring system is presented. The system generates a qualitative model of the student, which is able to evaluate information regarding student's knowledge and cognitive abilities based on their responses with a tutoring system for a subject specific domain area. More recently the work of [25] has used smooth support vector machine classification and kernel k-means clustering technique to analyse the relationships between student's psychometric behavioural factors and student success, as a means of deriving a model to predict performance.

Rule based approaches have been developed to identify quantitative and qualitative rules for describing patterns and associations in student behaviour and performance data. In [20] associative rules are mined to identify the probabilities of module failures based on association patterns of students prior failures in other subjects. A modelling and qualitative simulation methodology known as Fuzzy Inductive Reasoning (FIR) is proposed in [6] to generate logical rules for describing students learning behaviour based on a number of quantitative factors such as attendance, level of assistance required and average marks over different assessed components of the course. FIR uses predefined fuzzy sets to discretise the input data into an encoded 'qualitative' model, which is then used to find causal and temporal relationships between variables in order to generate a prediction model. The FIR model extracts logical numerical rules for describing the students learning behaviour pattern on a course in relation to their final mark. The systems has been shown to generate comprehensible and actionable rules from data, however the rules are specified as crisp numerical ranges of encoded values which could be less intuitively understood by end users. The rules parameters also do not include additional data mining quality measures such as support (generality) [32] and confidence (reliability) [32] of rules to provide additional information for educators to judge and rank the suitability of the inferred rules in supporting teaching decisions. Although these quality indicators have been used in [20] to express frequency and reliability of student failure combinations occurring in the data.

The majority of data mining approaches described above do not provide a means to automatically summarizing data while directly contending with data uncertainties and quality measures to output human-friendly information that can be easily interpreted and used to support teaching decisions. Fuzzy Logic Systems (FLSs) have been applied to a range of application areas in educational systems that include student modeling and evaluation of student academic performance [26][4][34][19][27]. FLSs provide transparent and flexible

model representations that allow for the handling of real world information imprecision through the use of linguistic quantifiers such as 'Poor' or 'High' [16]. FLSs represents a methodology for *computing with words* in which linguistic quantifiers describing fuzzy sets are combined with human readable If-Then rules [16]. The rules convey richer and more easily understandable Linguistic Summarization (LS) of patterns of association between the input attributes and output decisions or states found in the data [32]. The extracted fuzzy classification rules also have rule quality measures associated with each rule that can be used measure the strength of patterns found in the data and provide the ability to rank the top rules associated with particular output conditions.

In this paper we describe use of a fuzzy LS technique based on extracting fuzzy weighted If-Then rules from student learning activity and performance data. The rules provide a descriptive representation of relationships between the monitored student activity / engagement characteristics and achieved performance. We introduce a new scaled fuzzy weighting value for each rule that is calculated based on modifications of two well know data mining rule quality measures. The scaled fuzzy weighting value measures the strength of the rules in their modelling and representation of association patterns found in the data and can be used to rank the most prominent profile rules for decision-making. Scaling the rule weights accounts for any large variations in the numbers of data patterns belonging to different class groups making the weighting more accurate for handling large uneven datasets. The rules can be used to highlight associations between activity / engagement characteristics and achieved performance on tasks. This can help educators to more effectively monitor students' progress as well as provide personalised feedback to students for identifying misconceptions and gaps in knowledge that will improve their engagement and performance on the learning tasks.

We propose an intelligent framework for monitoring student performance during activity and problem based learning tasks. Our system uses software and hardware plug-ins for monitoring and capturing data on student activity and performance parameters over the duration of ALL and CSCL activities. Unsupervised learning in combination with fuzzy LS is proposed to discover groupings of common learning behaviours and performance characteristics, from which weighted fuzzy summarisation rules are extracted. The fuzzy rules can be used by educators to analyse students activity on tasks and construct personalised feedback to students based on their identified learning traits. The system would also adapt to new data based on new student cohorts' overtime.

We will present a case study and experiments in which we apply the fuzzy LS technique for evaluating the effectiveness of using a new Group Performance Model (GPM) to deploy ALL effectively in Master-level group activity tasks [2]. The experiments demonstrate how the fuzzy LS technique can be incorporated as part of our proposed automated intelligent analysis and feedback system.

### III. FUZZY LINGUISTIC SUMMARISATION APPROACH

We have used a Fuzzy LS approach consisting of four phases as shown in Fig. 1 and described below.

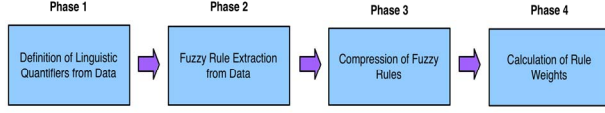


Figure 1. Flow diagram showing the phases of the fuzzy LS approach.

#### A. Definition of Linguistic Quantifiers from Data

In **phase 1** the input / output data collected from monitoring students on activity tasks is initially mapped to a defined set of linguistic quantifiers. These can be represented by Singleton, Crisp Interval or Fuzzy sets as shown in Fig. 2. For Boolean or categorical data attributes such as ‘Yes’ and ‘No’ or ‘Prior Programming in C++’, we use singleton sets as shown in Fig. 2a. For predefined crisp numerical ranges such as specific grade boundaries: ‘50-59%’, we use crisp interval sets as shown Fig. 1b. Both These types of linguistic quantifiers follow classical set theory where the membership of an element that belongs to a set is assessed according to a binary condition: either it belongs or does not belong to the set. So the boundary of such a classical set is crisp and defined by the following Membership Function (MF) [16]:

$$A \Rightarrow \mu_A(x) = \begin{cases} 1 & \text{if } x \in A \\ 0 & \text{if } x \notin A \end{cases} \quad (1)$$

where  $\mu_A(x)$  is a crisp MF for the set  $A$ .

In numerical and continuous valued data attributes, uncertainties pertaining to the linguistic quantification over different data values of the attribute require the use of fuzzy sets. This is a generalisation of a crisp set that allows the gradual assessment of the membership of an element belonging to a set by using a fuzzy MF as follows [35]:

Given a domain of discourse  $X$ , a fuzzy set  $A$  (shown in Fig. 1c) on  $X$  is a set expressed by a characteristic function  $\mu_A(x) : X \rightarrow [0,1]$  that measures the membership grade of the elements in  $X$  belonging to the set  $A$ :

$$A = \{(x, \mu_A(x)) \mid \forall x \in X, \mu_A(x) \in [0,1]\} \quad (2)$$

where  $\mu_A(x)$  is called the fuzzy MF of the fuzzy set  $A$ .

We aim to partition the accumulated students input / output activity and performance data into a set of MFs which quantify the values of the input and output attributes into linguistic labels that divides the input and output space into fuzzy / crisp regions. Each continuous variable’s space is partitioned into a number of overlapping triangular MFs covering the range of the input data values. This is achieved by applying a clustering algorithm such as k-means [14] on each input dimension to determine the centroids for each cluster that will represent the centre of each fuzzy set. Non-continuous valued attributes such as Boolean / categorical and interval ranges would be represented by singleton or

crisp interval MFs. The value of  $V$  defines the number of linguistic quantifiers which are to be extracted for each input and output variable where  $V^I$  is denoted for the input variables and  $V^O$  for the output variables.

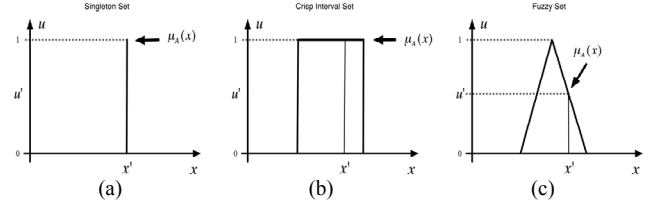


Figure 2. (a) A singleton set. (b) A crisp interval set. (c) A fuzzy set based on a triangular MF.

#### B. Fuzzy Rule Extraction from Data

In **phase 2** a fuzzy rule extraction approach based on the enhanced Mendel Wang method described in [29] is used. This is a one-pass technique for extracting fuzzy rules from the sampled data, which has been previously used in [7] for extracting fuzzy control rules. The data is mapped to the fuzzy / crisp sets for the antecedents and consequents of the rules generated in phase 1. For a fixed input / output attribute  $x^{(t)}$  in the sample dataset ( $t = 1, 2, \dots, N$ ), the membership values  $\mu_{A_s^q}(x_s^{(t)})$  are computed for each membership function  $q = 1, \dots, V^I_s$ , and for each input variable  $s$  find the set  $q^* \in \{1, \dots, V^I_s\}$ , such that

$$\mu_{A_s^{q^*}}(x_s^{(t)}) \geq \mu_{A_s^q}(x_s^{(t)}) \quad (3)$$

for all  $q = 1, \dots, V^I_s$  where  $s = 1, \dots, n$  and  $n$  is the number of inputs and  $N$  is the number of data instances [7]. The same process is repeated for the output variable  $y^{(t)}$  and its respective output fuzzy / crisp sets  $B^h, h = 1, \dots, V^O$  [7]. We use the approach to extract multi-input single-output antecedents and consequent combinations which describe the relationship between  $y^{(t)}$  and  $x^{(t)} = (x_1, \dots, x_n)^{(t)}$ , and take the following form:

$$\text{IF } x_1^{(t)} \text{ is } A_1^q \text{ and } \dots \text{ and } x_n^{(t)} \text{ is } A_n^q, \text{ THEN } y^{(t)} \text{ is } B^h \quad (4)$$

This process generates If-Then rule for each data instance, which will consist of duplicate rules.

#### C. Compression of Fuzzy Rules

In **phase 3** rule compression is performed on the data instance based rules in order to summarise the data into unique rules. This process involves a modified calculation of two rule quality measures from which we then derive the scaled fuzzy weight of each unique summarisation rule. The quality measures are based on *generality* which measures how many data instances support each rule [32] and *reliability* that measures the confidence level in the data

supporting each rule [32]. In our approach the rule generality is measured using *fuzzy support* and the reliability of the rule is based on calculating its *confidence*.

The *fuzzy support* of a rule is calculated as the product of the rule's *support* and *firing strength*. The support of a rule refers to coverage of data patterns that map to it [12], while its *firing strength* measures the degree to which the rule matches those input patterns [16]. The rule's *fuzzy support* can be used to identify the unique rules with the most frequent occurrences of data patterns associated with them, where the data patterns also most closely map to those rules. The fuzzy support of each rule is scaled based on the total data patterns for each output set so that the frequencies are scaled in proportion to the number data patterns found in each consequent set. The calculation of the scaled fuzzy support for a give uniquely occurring rule is shown in equation (5) and is based on the calculation described in [12]. In our fuzzy LS process it is used to identify and eliminates duplicate instance based rules to compress the rule base into a set of  $M$  unique and contradictory rules modelling the data.

$$scFuzzSup(\underline{A} \Rightarrow B^h)^l = \frac{\sum_{\underline{A} \in B^h} \prod_{s=1}^n \mu_{A_s^q}(x_s^{(l)})}{k^h} \quad (5)$$

where  $l=1,2,\dots,M$ ,  $l$  is the index of the rule,  $\underline{A}$  is the set of antecedent sets associated with the consequent set  $B^h$  and  $k^h$  is the total number of data instances that map to the consequent set  $B^h$ . The product t-norm over  $n$  calculates the firing strength of  $\underline{A}$  for the  $l^{th}$  rule.

The confidence of a rule is a measure of a rule's validity describing how tightly data patterns are associated to a specific output set. The confidence value is between 0 and 1. A confidence of 1 means that the pattern described in the rule is completely unique to a single output set. A confidence of less than 1 means that the pattern that is described in the rule occurs with more than one output set, and would then be associated with the output set with the highest confidence. The rule scaled confidence calculation is shown in equation (6) and is based on the calculation described in [12].

$$scConf(\underline{A} \Rightarrow B^h)^l = \frac{FuzzSup(\underline{A} \Rightarrow B^h)^l}{\sum_{\underline{A} \in B^h} \prod_{s=1}^n \mu_{A_s^q}(x_s^{(l)})} \quad (6)$$

where the scaled fuzzy support of each antecedent pattern  $\underline{A}$  associated with the consequent set  $B^h$  is divided over the total firing strengths of contradictory antecedent patterns  $\underline{A}$  that are not associated with  $B^h$ .

#### D. Calculation of Scaled Rule Weights

In **phase 4** the product of the scaled fuzzy support and confidence of a rule is used to calculate the rule's *scaled*

*fuzzy weight* as shown in equation (7).

$$scWi = FuzzSup \times Conf \quad (7)$$

Each of the generated  $M$  rules is assigned the scaled fuzzy weight measure  $scWi$  and takes the following form:

$$IF x_1 \text{ is } A_1^{(l)} \dots \text{ and } x_n \text{ is } A_n^{(l)}, THEN y \text{ is } B_1^{(l)} [scWi] \quad (8)$$

The scaled fuzzy weight measures the quality of each rule in modelling the data. It can be used to rank the top rules associated to each output set and choose a single winner rule among compatible rules based on methods for rule weight specification described in [12].

#### IV. PROPOSED INTELLIGENT FRAMEWORK FOR MONITORING STUDENT PERFORMANCE

In technology-enhanced learning when students attempt educational tasks they generate data of responses that is invaluable for understanding their learning behaviour, performance, learning styles and identifying their misconceptions about the subject. Currently this data is not systematically captured and analysed for making intelligent decisions for improving students' learning and adapting tutors' teaching in accordance with students learning styles, strength and limitations. Furthermore, the data is not used to support the learning of the next cohorts of students. We propose an intelligent framework for monitoring individual or group performance for activity and problem based learning tasks as depicted in Fig. 3.

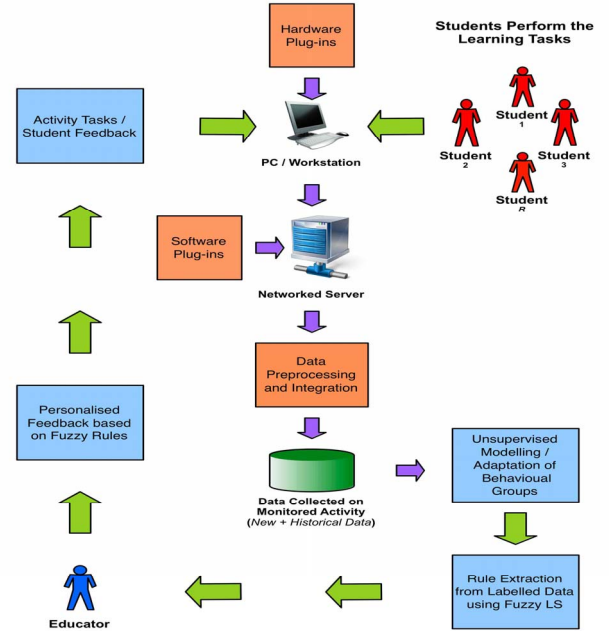


Figure. 3. Flow diagram showing the proposed student performance monitoring system.

The effective interpretation and analysis of data on student's activity and engagement characteristics can then be used by

educators to provide better guidance and feedback to students for improving performance. Our system starts with a process of automatically capturing engagement and performance data by monitoring students on learning tasks.

#### *A. Capturing Data from Software and Hardware Plug-ins*

We previously mentioned how software plug-ins can be used to capture data related to learners' task and activities. Other parameters will depend on the nature of activity. For example with the computer programming activity the software plug-ins would capture compilation attempts/errors, stack traces and name and number of source files and relationship between them. In addition hardware plug-ins can be used to capture cognitive and physiological parameters consisting of fixation duration, gaze position, and blink rate (from unobtrusive eye tracking systems), which will be used to infer learner's interest level, focus of attention and emotional state. These monitored activity parameters can be associated with students' performance on end of task quizzes and tests over the course of the activity. By monitoring both the learner's interaction with the development environment or application and other physiological indicators, we will be able to capture a rich range of behavioural and performance characteristics. This data will enable us to infer useful patterns pertaining to the underlying causes of learners' engagement, misconceptions and gaps in knowledge that affect their performance.

In our proposed framework the hardware plug-ins would be attached to laboratory workstations used by students to perform educational tasks, see Fig 3. Software tools and applications used during the activities would be run on the workstations in conjunction with the software plug-ins used to monitor students' interactions with the applications. The software tools and plug-ins would be hosted from a central server which would be also be used to capture integrate and pre-process the monitored data and store it in a database repository, as shown in Fig 3.

#### *B. Unsupervised Modelling of Learning Behavioural Groups*

The data stored in the repository would then be processed to discover the characteristics related to particular groups of learners, see Fig 3. These groups would represent learners with similar characteristics based on their behaviour, performance and cognitive abilities. Computational Intelligent (CI) approaches based on unsupervised learning can be used to model unlabeled dataset into a finite and discrete set of natural hidden data clusters [33]. The most prominent unsupervised CI approaches are the Self-Organising Map (SOM) [13] and the Adaptive Resonance Theory (ART) [5]. Each cluster would represent a set of data points in the multi dimensional feature space of the monitored parameters exhibiting common learning behaviours and performance. The identified clusters would be labelled along with the monitored data points based on their individual belongingness to each cluster.

#### *C. Rule Extraction from Labelled Data based on Fuzzy LS*

We propose to use the fuzzy LS approach described in section III on the labelled data to extract the fuzzy If-Then

summarisation rules for the multi-dimensional data points that make up each of the previously generated clusters, as shown in Fig 3. The fuzzy rules represent local linguistic summarisation models that capture the distribution of the intra-cluster data variations. The rules provide a means by which each cluster's behaviour / performance characteristics can be interpreted and represented in context of the distribution and variation of data points belonging to it. The quality of each rule is based on the rule's calculated scaled fuzzy weight measure, which can be used to rank the strongest rules describing student activity and behaviour characteristics pertaining to the specific discovered groups.

#### *D. Personalised Feedback based on Extracted Fuzzy Rules*

The rules can be easily interpreted and used by educators for analysing students behaviour, their progress on tasks and help to identify students who are not engaging and performing poorly on the activity. The fuzzy rules can provide a basis for educators to construct personalised feedback to students based on their identified behavioural and learning traits. The feedback will aim to identify misconceptions and gaps in knowledge that will help to improve their engagement and performance on the following learning tasks. The feedback can be fed back to students via the system and applications they are using to work through the activity see Fig. 3.

#### *E. Adaptation of Behaviour Groups based on New Data*

The system would perpetually be updated through the process of regenerating the data clusters and fuzzy LS rules by combining previous historical data with new data collected from new learners, see Fig 3. This will be done at periodic stages: when the activity is re-run for different student cohorts or due to assessing the quality of the model and the feedback produced by it. This process of perpetually regenerating the data model will also allow the system to identify trends in behaviour groups over different learner groups, which may be attributed to students' previous qualifications and backgrounds. Hence the feedback generated for these student groups can be targeted to include other forms of support.

## V. CASE STUDY AND EXPERIMENTS

Most of the pedagogical innovations of previous years have considered teamwork and the use of Information Communication Technology (ICT) that lead to the development of the Computer Supported Collaborative Learning (CSCL) activities [8], [24]. Activity-Led Learning (ALL) was initiated by Coventry University, UK to enhance students learning experience and address the problem of student satisfaction and retention rates. ALL is a pedagogic approach in which the activity is the focal point of the learning experience. An activity can be is a problem, project, scenario, case study, research question, classroom, or laboratory based activity for which a range of solutions or responses are appropriate. ALL requires a self-directed inquiry or research like process in which the individual

learner, or team of learners, seek and apply relevant knowledge, skilful practices, understanding and resources relevant to the activity domain to achieve appropriate learning outcome(s) in accordance with the programme of study [31]. ALL is also designed for collaborative learning tasks and group based activities encouraging students to form personal and social bonds.

When ALL is being used in its pure form, lecturers have a role of supportive facilitator rather than the traditional role of ‘expert’. This pedagogy leads to the development of a learning community involving staff and students [30]. Although ALL has many advantages as compared to the traditional didactic methods of module delivery (i.e. lectures and assessment by means of assignments and or examinations to test knowledge), it can produce poor results if not applied in a structured way and monitored carefully.

#### A. Group Performance Model for Facilitating ALL

GPM provides a structure within which students are introduced to the ALL methodology and are transformed from a number of individual learners into a cohesive group of collaborative colleagues that share common understanding within the context of the activity. The process is shown in Fig. 4 where we have applied it to student groups studying a Network Planning and Management module as part a postgraduate computer science course. In the initial stages of the process a self-assessment methodology was used for the evaluation of the learner where students assess their own knowledge of computer networking disciplines, to grade themselves and describe any relevant experience they have. The intention is to establish what elements might constitute ‘Common Ground’ between the students. This can be used to progress group formation and the assignment of roles and tasks, see Fig. 4.

Following these initial stages the process of Forming – Storming – Norming – Performing a well established group development model proposed by Tuckman in 1965 [28] was used to facilitate group processes. This was achieved through the use of directed CSCL activities based on investigating a series of case studies and maintaining a diary in which students would record their experiences in a group context and relate these to their reflections upon their learning and time spent on the task. This would enable “face to face” interaction on an inter-personal level to facilitate better group cohesions in performing activity tasks.

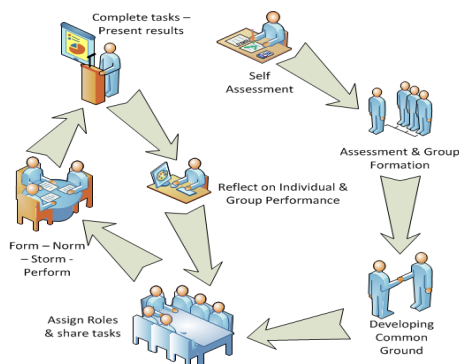


Figure. 4. Group Performance Model.

In the final stages of GPM the groups presented their case study solutions during a seminar, as shown in Fig. 4. Tutors interviewed and assessed groups individually on their technical knowledge of their case study solution, knowledge of their colleagues’ areas of responsibility and upon the processes their group followed to achieve their results. Groups were given individual and group feedback on their case study results prior to submission of the next case study to address any area of weakness or development. The groups were able to identify any issues in their group structure and allocation of responsibilities that prevented them achieving higher grades.

#### B. Group Performance Analysis using Fuzzy LS

Experiments were performed using the Fuzzy LS technique for modeling activity characteristics of student groups in relation to their performance on case study investigation they were required to perform as part of the module. The Fuzzy LS model was also used to evaluate the effect of GPM on group performance where GPM was applied to a selected number of groups. Data on 20 student groups, consisting of 110 students, engaged in CSCL activities related to the investigation of a single case study was acquired. The data consisted of three inputs, two continuous valued inputs namely: estimated time-on-task, actual time-on-task by a group and a Boolean valued input: GPM, indicating the presence or absence of applying GPM to the group. The single output of the data specified the percentage of marks achieved by the group.

The fuzzy LS approach was used to partition each of the two continuous input variable spaces into three triangular MFs defining the fuzzy sets for ‘Low’, ‘Medium’ and ‘High’, covering the range of the input data values. Fig. 5 shows the three fuzzy sets for the input variable estimated time-on-task. The Boolean valued input GPM was represented by crisp singleton MFs associated with a single point of maximum membership, in this case 0 or 1. The output was represented using three crisp interval sets for each of the percentage grade boundaries reflected in the data, specifically these were: 40 – 59 for *Pass*, 60 – 69 for *Merit* and 70 – 100 for *Distinction*.

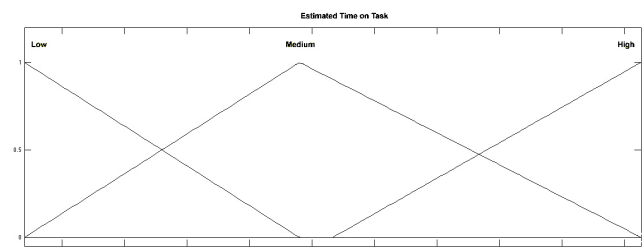


Figure. 5. Fuzzy sets for input variable Estimated Time on Task.

The fuzzy LS model generated 12 rules for summarising the data. The modeling accuracy of the generated LS model was checked on the original data where the model achieved 85% accuracy. Table I shows the top strongest profile rules describing group performance characteristics identified from the model. The rules are shown grouped according to each

output grade boundary and ranked in order of the calculated scaled fuzzy weight of each rule. The table in Fig. 6 also shows the support, scaled fuzzy support and confidence for each rule. The strongest rule for each output grade is also highlighted representing the pattern of input activity and engagement characteristics most strongly associated with each performance grade boundary.

TABLE I.  
STRONGEST FUZZY SUMMARISATION RULES DESCRIBING GROUP ACTIVITY CHARACTERISTICS FOR DIFFERENT GRADE BOUNDARIES

Estimated Time on Task	Actual Time on Task	GPM	Grade	Support	Scaled Fuzzy Support	Scaled Confidence	Scaled Fuzzy Weight
High	High	Not-Applied	Pass	2	0.31	1.00	0.31
Medium	Medium	Not-Applied	Pass	2	0.26	0.64	0.17
Low	Low	Applied	Pass	2	0.34	0.34	0.12
Low	Low	Applied	Merit	4	0.50	0.66	0.33
High	Medium	Not-Applied	Merit	2	0.15	1.00	0.15
Medium	Medium	Applied	Distinction	2	0.49	1.00	0.49
High	Medium	Applied	Distinction	1	0.30	0.50	0.15

The profile rules in table I show that the application of GPM overall resulted in reduction of the time that groups spent on performing their collaborative activity. Specific to each grade boundary: the top two rules describing profiles of groups who passed indicate that they spent considerably more effort / time (*High / Medium* estimated time-on-task and actual time-on-task) to achieve a pass grade when GPM was not applied. The third top rule refers to the condition in which GPM was applied and shows that groups in this profile spent less effort / time (*Low* estimated time-on-task and actual time-on-task), to achieve the same grade.

The model produced two top rules for groups obtaining a merit. These shows that the profile of groups where GPM was applied spent *Low* estimated time-on-task and actual time-on-task, compared to the profile of groups where GPM was not applied. Finally the top two profiles of groups for distinction indicate that only those groups gained distinction in which the GPM was applied. The groups associated with these profiles achieved better results (i.e. a distinction) even by spending approximately the same amount of effort / time as groups associated with the profiles in lower grade boundaries (pass and merit) where GPM was not applied.

Time-on-task has been considered as one of the measures of students' engagement in the CSCL activities [22] and a predictor of performance [9] [1]. These results show that the application of GPM has helped students better engage in their group activities and systematically improve the quality of time spent on tasks, while reducing time otherwise required for dealing with inter personal issues and coordination of activities. These groups also show better performance across all grade boundaries.

The study also recognised that groups that spent more time-on-task but scored poor performance grades, were unable to establish proper common ground. The analysis of these groups revealed obstacles such as the cost of coordination of group work and spending of left over time, especially working on the case study after four hours of intensive class work, when they felt fatigued. They also lacked drive, direction and as a result requested more time to complete the case studies. The time they spent unsuccessfully on seeking to resolve issues like determining

a group leader, assigning and coordinating tasks prevented them from engaging fully with the case study, and hence affected their performance. The conclusion reached is that a failure to establish 'common ground' in a structured manner impacted upon their wider group behaviours. The results produced from this analysis were also consistent with the lecturer's expectations on groups' performance through the application of a structured and directed group formation and activity process such as GPM.

Although the presented results are quite preliminary, and based on a small set of variables, the analyses demonstrate how the application of the Fuzzy LS was able to provide linguistically interpretable rules that were used to quickly and easily identify association patterns between activity characteristics and performance from student data on CSCL activities.

## VI. CONCLUSIONS

In this paper we describe the use of a fuzzy linguistic summarisation technique for extracting linguistically interpretable fuzzy weighted rules from student data describing useful relationships between activity / engagement characteristics and achieved performance of students. The technique is based on extracting scaled fuzzy weighted If-Then rules from the data that provide a descriptive and easily interpretable representation of the most prominent association patterns between the monitored student activity / engagement parameters and achieved performance.

We have proposed an intelligent framework for monitoring individual or group performance of students during activity and problem based learning tasks. Our system would use software and hardware plug-ins for monitoring and capturing data on student activity and performance parameters over the duration of group based ALL and CSCL activities. An adaptive unsupervised learning technique would be used to discover data clusters of common learning behaviours and performance characteristics. The fuzzy LS would be used to extract weighted fuzzy rules from the clustered labelled data. The interpretable rules can be used by educators to analyse students behaviour on tasks and construct personalised feedback to students based on their identified learning behaviour traits in order to improve their performance.

We conducted group performance analysis using the fuzzy LS approach to evaluate the effectiveness of using GPM to deploy ALL effectively in a group activity tasks performed by students on a postgraduate Network Planning and Management module. The fuzzy LS approach was able to extract summarization rules which showed that the application of GPM overall resulted in reduction of the time that groups spent on performing their collaborative activity while achieving better performance. The experiments demonstrate how the fuzzy LS approach can be used to effectively monitor students' progress and performance, allowing educators to transparently evaluate teaching processes and factors effecting student engagement in ALL.

For our future work we plan to conduct extensive analysis



of students learning behaviours by monitoring parameters on the learners' activity, emotion, personality traits and performance derived within the framework of our proposed performance monitoring system. Due to the various types of uncertainties present in such data we aim to explore the use of type-2 LS approaches [17] for modelling these uncertainties. The high dimensionality of the proposed data will also require us to investigate various feature selection approaches for selecting the most prominent and useful data parameters. We plan on investigating unsupervised learning techniques that would be used in combination with fuzzy LS to discover and learn student activity and performance behaviour grouping to recommend personalised feedback to students based on their learning patterns.

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