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# Student and Group Activity Level Assessment in the ELARS Recommender System

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***Abstract*****—**This paper presents an original approach to student and group activity level assessment that relies on certainty factors theory. Activity level is used to represent quantity and continuity of student's contributions in individual and collaborative e-learning activities (e-tivities) and is calculated to assist teachers in assessing quantitative aspects of student's achievements. Calculated activity levels are also used to raise awareness and provide recommendations during the learning process. The proposed approach was implemented within the educational recommender system ELARS and validated using data obtained from e-tivity realized during a blended learning course. The results showed that the proposed approach can be used to estimate activity level in the context of e-tivities realized using Web 2.0 tools as well as to facilitate the assessment of quantitative aspect of students' participation in e-tivities.

***Keywords*****—**Assessment, ELARS, e-learning, recommender systems, student model.

## I. Introduction

IN adaptive and intelligent educational systems, service is tailored to student's knowledge, goals, communication skills, and interests [1]. The quality of these systems depends on their student modeling, regardless of the techniques used. An approach referred to as e-learning 2.0 [2], [3] tends to openness and assumes the usage of different tools available on the Web, which affects the phases of creation and update of the student model. Therefore, the ability to manage distributed information in the process of student modeling is very important [4]. Besides student model, an important part of today's educational systems that supports collaborative learning is the group model [5].

This paper presents a research on implementing student activity level assessment in an e-learning 2.0 environment that consists of a learning management system (LMS), a set of Web 2.0 tools and educational recommender system ELARS [6], [7]. A student and a group activity level, as a part of student and group model in ELARS, represent quantity and continuity of student's contributions to the e-learning activities (called e-tivities [8]) which are realized using Web 2.0 tools. The aim of activity level assessment is to assist teachers in assessing quantitative aspects of student's achievements as well as to provide recommendations in the context of e-tivities and ensure awareness support in the ELARS system.

The presented research contributes to the field of student modeling by proposing an innovative approach for activity level assessment during (collaborative) e-tivities that are realized using Web 2.0 tools. In order to address uncertainty, which is one of the important problems in the field of student modeling [9], the approach takes advantage of the certainty factors theory. Activity level assessment is based on expert's (and/or teacher's) knowledge and the collected data and calculated relative to other students' contributions. In order to interpret the collected data so it becomes meaningful for the adaptive system, designed categorization method for representing student's interactions with Web 2.0 tools is used.

The paper is organized as follows. Section II gives background information on approaches and technologies that can support collaborative learning, and Section III outlines the structure of the e-learning environment used in the research. Section IV presents approach to implementation of activity level assessment. The results of the conducted experiment are presented in Section V, while Section VI concludes the paper and gives guidelines for future work.

## II. Background

Many adaptive systems reflect the "teaching" perspective where the primary goal is delivering course materials. Recent research in the field emphasizes collaborative learning and aims to the so called "learning" perspective. This student-centered model based on the constructivist theory of learning assumes that students are offered the opportunity to construct knowledge through active participation in e-tivities [10]. To perform a certain e-tivity, students can use different tools and work by themselves or be divided into groups [11]. The e-learning 2.0 approach [12] emphasizes the need for collaborative learning and the usage of so-called Web 2.0 tools that foster creation of Web resources as well as sharing and communication with peers [13], [14].

Among the technologies that could be used for adaptive interventions in the described context, recommender systems should be considered. Those systems support efficient use of available learning resources and therefore support achievement of expected learning outcomes [15]. Recommender systems provide recommendations based on data regarding student's characteristics, previous actions and achievements, as well as on data regarding similar students. Therefore, their student model should comprise all the data necessary for adaptation [16]. Since recommendations can be intended for groups as well, an important part of the recommender system aimed at collaborative learning is a group model. The group model can be created based on individual models by using aggregation mechanisms or by

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observing interactions of a group as a whole [17].

Except for recommending potentially useful resources (which can include learning materials, collaborators, tools, etc.), data from student and group models can be used for encouraging students' participation and collaboration in e-learning 2.0 environments. Such adaptive interventions should not be neglected, since the level of online participation is significantly related to students' learning achievements [18].

During collaborative e-tivities student's actions may or may not be visible to all participants (all group members). Therefore, there is a need for implementation of awareness mechanisms in order to help students maintain a representation of other students' engagement which might have a positive impact on their meta-cognitive activities [19], [20]. Awareness mechanisms can disturb student's activity, which is related to his/her attentional state. Thus, timing is one of the parameters that need to be considered during the implementation of the awareness support.

## III. E-Learning 2.0 Environment Overview

The online learning environment used in this research consists of an LMS (e.g. Moodle, Canvas by Instructure) and a set of Web 2.0 tools. LMS is used to deliver learning materials and for communication between teachers and students, while Web 2.0 tools are used for e-tivities. The initial set of Web 2.0 tools is shown in Table I and it was chosen to allow the realization of different types of e-tivities [7]. In addition, the e-learning 2.0 environment (Fig. 1) is extended with the ELARS recommender system in order to ensure personalization [21].

Below, the purpose of the main system components is outlined, in respect to the activity level assessment procedure.

### *A. Activity Model*

The activity model represents course learning design – a workflow of activities in which students should participate in, in order to achieve the planned learning outcomes. Course learning design is defined by a teacher, usually with the help of e-learning designer who is familiar with the systems' functionalities. Learning design serves as basis for activity level assessment. Representations of Web 2.0 tools included in the e-learning environment and pre-defined set of advice are stored in the activity model as well. Activities are classified into six categories and grouped in learning modules which are represented with a directed graph (examples can be seen in Section V).

The most important category is *e-tivity realized using Web 2.0 tool* (eLA). Each e-tivity $eLA_i$ is represented with tools which are offered to perform the e-tivity and a set of parameters that enable activity level assessment (described in Section IV). These parameters should be defined in collaboration of teacher and expert (e-learning designer) during the course learning design definition. E-tivities can be part of summative and/or formative assessment. However, they cannot be automatically evaluated. Therefore, the teacher needs to decide upon the number of points that will be given to each student according to the criteria that can include quality and quantity of their contributions.

Beside e-tivities (eLA), learning modules can contain *content learning activities* (CA) to foster students' interaction with learning materials and *testing activities* (TA), both performed in the LMS. In addition, activities performed in the ELARS are: *decision activities* (DA) within which students choose between recommended items and *support activities* (SA) for delivering instructions, questionnaire results, input data needed for activity level assessment, etc. [7].

### *B. Subsystem for Student and Group Modeling*

Using the module for collection and pre-processing of data, as well as the module for student and group modeling, knowledge about students and groups is acquired and stored in the student and the group model. The student model contains data on four student's characteristics [7]: preferences of Web 2.0 tools, preferences of learning styles according to VARK model [22], knowledge level, and activity level. Group model contains only data regarding activity level. Other characteristics are not represented at group level.

Activity level is automatically calculated based on the data collected from Web 2.0 tools, as described in Section IV.

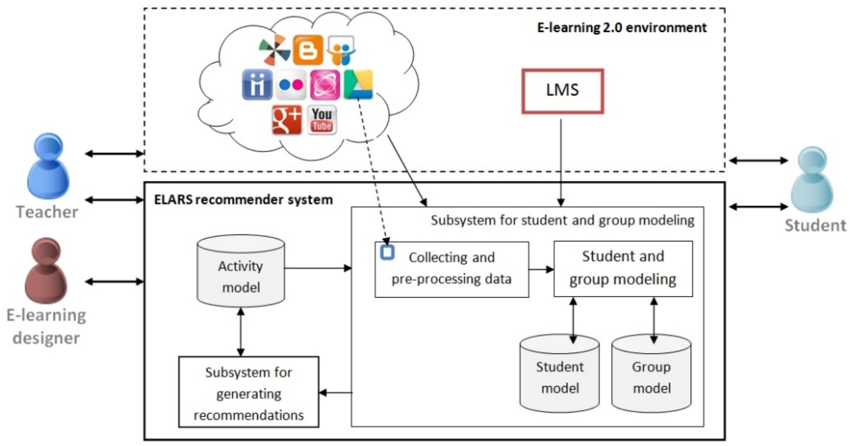


Fig. 1 The structure of the e-learning 2.0 environment

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The values are initialized before the e-tivity starts and are dynamically updated at the end of each defined interval (the intervals are used to determine if student's participation is continuous or not). Activity level is represented in accordance with the structure of learning design using a two-level overlay model [23]. At the first level, numerical values that represent the estimation of student or group activity level are associated with e-tivities within a learning module. The second level refers to modules within the course learning design.

The data from the student and the group model are combined with data from the activity model in order to ensure awareness and provide recommendations to students during the learning process. In addition, computed data are available to the teacher to enable monitoring and to support assessment (grading) of quantity and continuity of their contributions.

### C. Subsystem for Generating Recommendations

The ELARS system supports students while selecting offered e-tivities, collaborators and Web 2.0 tools for their realization [24]. Therefore, this subsystem calculates the value of usefulness for all possible items in order to rank them. Usefulness of recommended e-tivity or collaborator is calculated in relation to the students' characteristics including activity level. In the case of collaborators recommendation, for example, usefulness is expressed by a similarity measure between students, so it is possible for the teacher to define the criteria that would encourage grouping of students that are (not) similar regarding the activity level for a certain e-tivity.

The system also enables awareness support. Students have an insight into their own activity level and, in case of a group-based activity, the activity level of their group (Fig. 2). By presenting these values to students at the end of each defined interval, they are able to compare their own results over time and become aware of whether they are progressing or not. Making students aware of other students' results during an e-tivity is also important, especially for the collaborative learning. Thus, besides their own results, students are able to see activity levels of all other participants. In case of group-based activities, students have an insight into the activity levels of their group members and the activity levels of other groups in order to compare their own performance with others. Calculated activity levels are accompanied with corresponding advice. Variables in the pre-defined set of rules used to generate them include student/group activity level and their change over time. For example, the advice for a successful student is that he/she should keep up the good work, but should also try to encourage certain inactive group members to participate. At the end of the last interval, advice is related to future e-tivities.

## IV. Activity Level Assessment

### A. Data Collection

The first phase of activity level assessment is the collection of adequate data. While working with Web 2.0 tools in order to complete specified tasks, students perform different actions. The piece of data that represents student's interaction with the learning environment during an e-tivity is referred to as an activity trace [25]. Every activity trace corresponds to one student's contribution and is retrieved via RSS feeds or API requests from Web 2.0 tools included in an e-learning 2.0 environment. Therefore, the system setup included the development of procedures specific to each Web 2.0 service that are part of the module for collection/preprocessing of data.

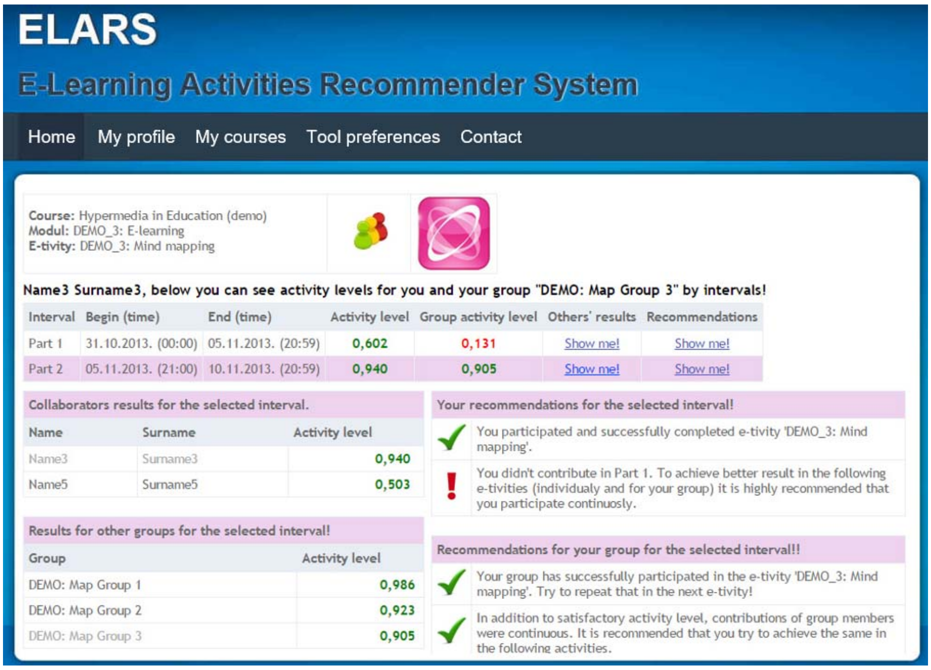


Fig. 2 The page from student's interface with activity levels and recommendations

TABLE I
DATA FOR DETERMINING ACTIVITY TRACE WEIGHTS

| | Web 2.0 tool | Updating | Commenting/Posting messages | Tagging | Sharing |
|---|---|---|---|---|---|
| 1. | Blogger | Number of words | Number of words | - | 1 |
| 2. | Diigo | 1 | - | Number of words | - |
| 3. | Flickr | 1 | Number of words | Number of words | 1 |
| 4. | Google+ | 1 | Number of words | - | 1 |
| 5. | Google Docs | Number of words | - | - | 1 |
| 6. | MindMeister | 1 | - | - | 1 |
| 7. | SlideShare | Number of slides | - | Number of words | 1 |
| 8. | Wikispaces | Number of words | Number of words | - | 1 |
| 9. | YouTube | Number of seconds | Number of words | - | 1 |

"- ": This action cannot be determined based on available data obtained from the respective service.

For some services, API credentials (e.g. consumer key and shared secret) provided by the service are needed in the process of authentication, as well as implementation of protocols for secure API authorization including OAuth 2.0 protocol [2]. To identify student's activity traces, the metadata of the created and published content is analyzed. Depending on the third-party service API, retrieved data can be in different structured or semi-structured formats, usually in XML or JSON. Student's actions are collected using input data provided by the student: his/her user identity (username or ID) and feed needed to identify his/her content related to the e-tivity (document ID, RSS feed, a given tag or similar). Regarding this phase, students are informed which kind of activity data is collected and for what purpose, as well as that the collected data will only be used within the system to enhance their learning.

### B. Interpretation of Collected Data

The collection of data is followed by interpretation in order to acquire its meaning for the ELARS system. Usage actions on content created and published during e-tivities are classified into several categories that are used as the basis for activity level estimation: updating, commenting/posting messages, tagging, and sharing. A category for every collected trace is determined in order to enable evaluation of different actions. If needed, this classification can be extended with new categories. In order to allow the increase of an activity level in accordance with the quantity of contribution, trace weights are determined as well (the number of words in a text, the number of slides in a presentation or seconds in a video). It should be emphasized that for some tools there are actions that can be performed but it is not possible to collect corresponding activity trace from third party services (e.g. comments in SlideShare). Table I shows which actions can be identified (sharing is observed using data retrieved from Google+) and the way of calculating trace weights for a given set of services. In case the quantity cannot be distinguished, all activity traces are considered equal and their trace weight is set to 1 (for example, photos on Flickr). This procedure is not robust to fake activity data so if a student publishes content or performs actions that are not related to a given task, the assessed activity level will not correspond to the actual state of his/her activity. At this point this problem is not addressed in a way that would enable automatic correction of calculated activity levels (e.g. in terms of penalty factors or similar). However, the teacher has to assess quality of created content, so he/she has insight into students' contributions in Web 2.0 tools as well as saved activity traces and is authorized to delete them. In addition, during group-based activities, other group members can also report to the teacher someone's fake behavior.

### C. Student and Group Activity Level Assessment

In the third phase, the activity level of a particular student is estimated. In case of a group-based e-tivity, activity level is estimated for each group as well.

When assessing students' work according to the predefined criteria, teachers can reason in terms of gathering evidence on whether the criteria have been fulfilled and to which extent. One can draw a parallel between this task and the formalism of the certainty factors theory that presumes gathering evidence that supports/contradicts a particular hypothesis [26]. Collected activity traces serve as evidence of student's activity based on which the activity level can be increased. On the other hand, in case there is a lack of this kind of evidence, the value of student's activity level can be decreased. This reasoning mechanism is suitable for the context of activity level assessment since it enables the definition of several rules that can lead to the same conclusion.

Rules that model knowledge regarding student's activity level estimation have the following form: ***if** there is an evidence of a student's activity related to the e-tivity* $eLA_i$ ***then** the student actively participates in the e-tivity* $eLA_i$. Based on the classification of possible student actions used for activity trace collection, concrete rules are formed using the antecedents listed in Table II. Every antecedent determines one evidence category. For example, one of the rules is: ***if** a student updated content related to the e-tivity* $eLA_i$ ***then** the student actively participates in the e-tivity* $eLA_i$. Those rules can be applied incrementally as new evidence becomes available. In addition, the mechanism can manage evidence with different degrees of belief [27].

A certainty factor $cf_r$ assigned to the rule $r$ for the e-tivity $eLA_i$, denotes the estimation to what extent would belief or disbelief in the hypothesis *the student actively participates in the e-tivity* $eLA_i$ be increased in case the corresponding evidence is found. By assigning positive certainty factors to the rules, different student's contributions (updating, commenting, tagging, and sharing) can be assessed differently. A higher value of a certainty factor will result in a greater increase in an activity level. On the other hand, negative values of certainty factors will result in a decrease and can be interpreted as a penalty for not participating (non-participation can be determined at the end of each interval). If there is no need for certain categories of evidence to affect the activity level, certainty factors of respective rules should be set to 0.

TABLE II
EVIDENCE CATEGORIES

| Evidence of activity | Evidence of a lack of activity (interval) |
|---|---|
| Student updated content. | Student did not update any content. |
| Student posted comment/message. | Student did not post any comment/message. |
| Student tagged content. | Student did not tag any content. |
| Student shared content on social network. | Student did not share any content on social network. |

Apart from certainty factors of the rules, total belief or disbelief in the hypothesis also depends on the evidence uncertainty. Certainty factors of found pieces of evidence, $cf(e_j)$, are automatically calculated based on the average trace weight for the used rule in order to eliminate the influence of number of traces on the value of an activity level. If we considered every trace as equal in the process of finding evidence, a student who made a lot of minor updates would have a significantly higher activity level compared to a student who made only a few updates, but wrote more words overall. When a piece of evidence $e_j$ is found, the matching rule $r$ is applied and a student activity level $a_i$ is calculated using (1).

$$a_i = cf(h, e_j) = cf(e_j) \cdot cf_r \tag{1}$$

Since all the rules used for activity level estimation have the same consequence, the individual certainty factors obtained from these rules can be combined. A combined certainty factor for a hypothesis is calculated by using (2). Equation (2) is applied incrementally as new evidence $e_l$ becomes available in order to update the value of the activity level [27]. The value $a_i$ ranges from -1 (student activity level for $eLA_i$ is low) to 1 (student activity level for $eLA_i$ is high).

$$a'_i = \begin{cases} \mathrm{a_i} + (1 - \mathrm{a_i}) \cdot cf(h, e_l), & if \quad \mathrm{a_i} > 0 \wedge cf(h, e_l) > 0 \\ \mathrm{a_i} + (1 + \mathrm{a_i}) \cdot cf(h, e_l), & if \quad \mathrm{a_i} < 0 \wedge cf(h, e_l) < 0 \\ \dfrac{\mathrm{a_i} + cf(h, e_l)}{1 - (\min(|\mathrm{a_i}|, |cf(h, e_l)|)}, & otherwise \end{cases} \tag{2}$$

For all group-based e-tivities, analogous procedure is performed. Rules used for student activity level estimation are rephrased to the following form: ***if** there is evidence of a group member's activity related to the e-tivity $eLA_i$ **then** the group actively participates in the e-tivity $eLA_i$*. Certainty factors for the rules concerning group activity level $cfg_r$ can remain the same as in student activity level estimation ($cfg_r = cf_r$) or the value $cf_r$ can be divided by the number of group members ($cfg_r = cf_r/m$). This decision depends on whether contributions from every group member are expected or not. In case every student is expected to contribute, for example to edit a group wiki page in Wikispaces, then $cf_r$ should be divided by the number of members in the group. This ensures that activity levels for diverse groups can be compared even in the case of different number of members. On the other hand, a planned activity can presume the contribution of just one group member, for example uploading a group presentation to SlideShare. In this case, the certainty factor should be set to a fixed value since the increase in the group activity level when evidence of such contribution is found, should not depend on group size.

The activity level of the learning module $LM_k$ is determined for each student (value $am_k$) and in case of group-based activities for each group (value $amg_k$). Calculation is based on activity levels for all e-tivities in the module $LM_k$ and corresponding weights $wa_i$ defined in the learning design. Initially, values $am_k$ and $amg_k$ are set to 0 and updated at the end of each interval.

## V. EVALUATION

In order to validate the approach for activity level assessment described in this paper, data from the blended learning course "Multimedia and Hypermedia Systems" were used.

### A. Context

The course "Multimedia and Hypermedia Systems" was designed for the graduate program in Computer Science at the Department of Informatics, University of Rijeka, Croatia. After completing this course a student should be able to analyze and identify different kinds of multimedia and hypermedia applications, as well as plan, design, develop and evaluate multimedia and hypermedia software for business or education purposes. The learning design of the course consists of six learning modules, as shown in Fig. 3.

To validate the proposed approach, the obtained activity levels for the e-tivity in the learning module "Learning diary" were analyzed. This module is performed in parallel with the module "Web application development" where groups of students have to develop a Web application for business or education. Activities included in the module "Learning diary" are shown in Fig. 4. Students (N=27) were supposed to take notes in the form of a diary. First, students were presented with the task, the expected results and evaluation criteria within support activity "Instructions". They had a chance to choose one of the offered Web 2.0 tools (Blogger, Wikispaces or Google Drive) according to recommendations presented in the corresponding decision activity and then asked to enter input data (user identity and feed) within support activities.

During the e-tivity, which lasted for seven weeks, students were expected to write their reflections on group project work, emphasizing their role within the group.

Rules used for activity level assessment with assigned certainty factors $cf_r$ are shown in Table III.

TABLE III
CERTAINTY FACTORS ASSIGNED TO RULES

| | Rules | $cf_r$ |
|---|---|---|
| $r_1$ | If student *updated content* related to $eLA_1$ then the student is actively participating in $eLA_1$. | 0,15 |
| $r_2$ | If student *did not updated any content during interval* related to $eLA_1$ then the student is actively participating in $eLA_1$. | -0,15 |

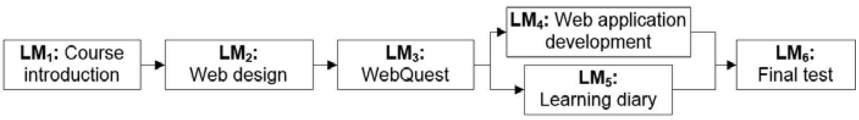


Fig. 3 Learning modules of the course "Multimedia and Hypermedia Systems"

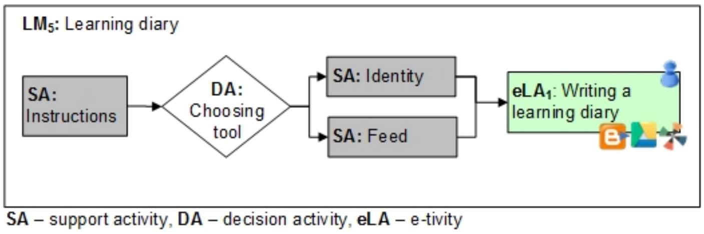


Fig. 4 Activities of the learning module "Learning diary"

*B. Method*

The main research questions were:

RQ1) Can estimate values represent student activity level in relation to other students enrolled into the activity, or group members in case of a group-based activity?

RQ2) Does the set of defined rules enable evaluation of different categories of contributions and continuous participation in the e-tivity?

RQ3) Does the choice of a particular tool affect activity level estimation in case of e-tivities in which a student can choose between several tools?

RQ4) To what extent obtained values coincide with the teacher's assessment of student's activity level?

To address the research questions stated above, activity levels and associated data for the e-tivity "Learning diary" were analyzed. To examine whether the estimated values represent student activity level relative to other students (RQ1), comparison of the sum of trace weights by categories, the overall number of found activity traces and the number of intervals in which activity traces were found for each student was performed.

While comparing trace weights by categories and in relation to the number of intervals in which traces were found, it was analyzed whether the set of defined rules enables evaluation with respect to different contributions and time aspect (RQ2).

In order to address RQ3, the comparison of activity levels for students that chose different tools, but have approximately the same values of other parameters, was done.

To address the RQ4 and identify the potential of the used approach for supporting teachers when deciding on the number of points regarding the quantitative aspect of participation, the following experiment was carried out. Participants were teachers from the Department of Informatics, University of Rijeka, Croatia (N=18). Teachers were asked to grade student's activity on a scale from 0.0 to 5.0 based on the number of written words and number of intervals. In addition, data used by e-learning designer for determining the *cf* factors were available: the expected number of words was (1800), the number of intervals in which student's activity is expected (4), and the ratio between $r_1$ and $r_2$ (4:1). In order to get the predicted grade, activity level $a_1$ was scaled to the segment [0,5] and rounded to one decimal place in the case of $a_1 \geq 0$. In the case of a negative value, $a_1 < 0$, the predicted grade was set to 0.

*C. Results*

Table IV shows the final results of activity level estimation ($a_1$) for each student, sorted in descending order and rounded to two decimal places. The period of seven weeks was divided into seven intervals, so the student activity level was updated at the end of each week. A total of 26 out of 27 students participated in this e-tivity. The table also shows the chosen tool, the number of written words, which represent the sum of trace weights, the number of intervals in which traces of student activity were found and the total number of discovered activity traces regarding eLA1.

The test correlation of teacher's grades with predicted grades, Shapiro-Wilk test of normality was performed in order to test distribution of data. The test showed that the data is not normally distributed (W=0.86, $p<0.05$), so non-parametric Spearman's R correlation test was performed in order to identify the strength of a relationship between teachers' and predicted grades. The test showed that teachers' grades significantly correlate with predicted grades ($R_s$=0.931, $p<0.01$). In addition, mean average error (MAE) and mean square error (MSE) were calculated per student (Table V) and per teacher together with the coefficient of determination R-squared (Table VI).

TABLE IV
RESULTS OF STUDENT ACTIVITY LEVEL ESTIMATION

| Student | Chosen tool | Words | Intervals | Traces | $a_1$ |
|---|---|---|---|---|---|
| s1 | Blog | 2827 | 4 | 9 | 0.99 |
| s2 | Wikispaces | 1685 | 5 | 20 | 0.93 |
| s3 | Blog | 1585 | 7 | 10 | 0.93 |
| s4 | Wikispaces | 1412 | 5 | 11 | 0.88 |
| s5 | Wikispaces | 1130 | 6 | 15 | 0.85 |
| s6 | Wikispaces | 1510 | 3 | 12 | 0.85 |
| s7 | Wikispaces | 1052 | 4 | 6 | 0.74 |
| s8 | Wikispaces | 918 | 4 | 5 | 0.68 |
| s9 | Blog | 825 | 4 | 6 | 0.66 |
| s10 | Wikispaces | 909 | 3 | 3 | 0.62 |
| s11 | Wikispaces | 931 | 3 | 4 | 0.61 |
| s12 | Wikispaces | 770 | 3 | 6 | 0.57 |
| s13 | Wikispaces | 650 | 4 | 11 | 0.49 |
| s14 | Google Drive | 300 | 6 | 7 | 0.30 |
| s15 | Wikispaces | 652 | 2 | 7 | 0.28 |
| s16 | Wikispaces | 186 | 6 | 7 | 0.15 |
| s17 | Google Drive | 491 | 4 | 7 | 0.15 |
| s18 | Google Drive | 260 | 5 | 7 | 0.13 |
| s19 | Google Drive | 347 | 4 | 9 | 0.09 |
| s20 | Wikispaces | 256 | 4 | 6 | -0.02 |
| s21 | Wikispaces | 304 | 3 | 7 | -0.08 |
| s22 | Wikispaces | 311 | 2 | 7 | -0.16 |
| s23 | Wikispaces | 131 | 4 | 6 | -0.23 |
| s24 | Google Drive | 93 | 4 | 4 | -0.27 |
| s25 | Wikispaces | 171 | 3 | 4 | -0.29 |
| s26 | Wikispaces | 252 | 2 | 4 | -0.30 |
| s27 | - | 0 | 0 | 0 | -0.68 |

TABLE V
ERROR MEASURES (PER STUDENT)

| Student | $a_1$ | Predicted grade | Teachers' grade | |
|---|---|---|---|---|
| | | | MAE | MSE |
| s1 | 0.99 | 5.0 | 0.03 | 0.01 |
| s2 | 0.93 | 4.7 | 0.27 | 0.07 |
| s3 | 0.93 | 4.7 | 0.3 | 0.11 |
| s4 | 0.88 | 4.4 | 0.41 | 0.19 |
| s5 | 0.85 | 4.3 | 0.67 | 0.67 |
| s6 | 0.85 | 4.3 | 0.58 | 0.44 |
| s7 | 0.74 | 3.7 | 0.51 | 0.32 |
| s8 | 0.68 | 3.4 | 0.49 | 0.35 |
| s9 | 0.66 | 3.3 | 0.84 | 1.05 |
| s10 | 0.62 | 3.1 | 0.64 | 0.54 |
| s11 | 0.61 | 3.1 | 0.61 | 0.51 |
| s12 | 0.57 | 2.9 | 0.93 | 1.21 |
| s13 | 0.49 | 2.5 | 0.49 | 0.32 |
| s14 | 0.3 | 1.5 | 0.77 | 0.75 |
| s15 | 0.28 | 1.4 | 0.42 | 0.25 |
| s16 | 0.15 | 0.8 | 0.52 | 0.35 |
| s17 | 0.15 | 0.8 | 1.08 | 1.45 |
| s18 | 0.13 | 0.7 | 0.42 | 0.23 |
| s19 | 0.09 | 0.5 | 1.02 | 1.2 |
| s20 | -0.02 | 0.0 | 0.34 | 0.3 |
| s21 | -0.08 | 0.0 | 0.42 | 0.45 |
| s22 | -0.16 | 0.0 | 0.38 | 0.43 |
| s23 | -0.23 | 0.0 | 0.11 | 0.11 |
| s24 | -0.27 | 0.0 | 0.11 | 0.11 |
| s25 | -0.29 | 0.0 | 0.07 | 0.05 |
| s26 | -0.3 | 0.0 | 0.08 | 0.04 |
| s27 | -0.68 | 0.0 | 0 | 0 |
| Average: | | | 0.46 | 0.43 |

MAE - Mean Average Error, MSE - Mean Square Error

## D. Discussion

Regarding RQ1, the results have shown that obtained values represent the student activity level relative to other participants. By comparing computed activity levels for any two students with approximately the same number of written words, it can be observed that the student who was active during more intervals will have a higher value. The difference between values is smaller when activity levels are closer to the maximum value of 1, because of the asymptotic increment.

Further analysis revealed that certainty factors assigned to the rules can be used to define the extent to which active participation includes continuous participation (RQ2). Higher certainty factors assigned to the rules have resulted in higher activity levels (students were more rewarded for their contributions, but less penalized for non-participation). Trace weights calculation according to the number of words and dynamic updates of the evidence certainty factors ensured that the number of contributions (the total number of traces) did not significantly affect the overall result. By comparing the estimated values for students with approximately the same number of contributions made in the same number of intervals, it can be observed that the activity level will depend on the number of written words. Minor variations in the overall results are possible because of the relative calculation of evidence certainty factors, meaning that student contributions with the same number of words written in different intervals can be evaluated differently. Consequently, the student who was contributing during the intervals when others were not, can have a higher activity level, especially if that occurs at the beginning of the e-tivity, since the average trace weight (and therefore evidence certainty factor) will be determined based (mainly) on his/her contributions. A significant impact of the selected tool on the overall result was not observed, which is relevant for RQ3. This was expected considering that the number of written words can be determined for each of the offered tools.

TABLE VI
ERROR MEASURES AND R-SQUARED (PER TEACHER)

| Teacher | Teachers' grade | | |
|---|---|---|---|
| | MAE | MSE | R-squared |
| t1 | 0.39 | 0.39 | 0.91 |
| t2 | 0.40 | 0.26 | 0.94 |
| t3 | 0.63 | 0.73 | 0.83 |
| t4 | 0.56 | 0.63 | 0.82 |
| t5 | 0.42 | 0.28 | 0.92 |
| t6 | 0.30 | 0.27 | 0.93 |
| t7 | 0.33 | 0.20 | 0.95 |
| t8 | 0.32 | 0.24 | 0.93 |
| t9 | 0.54 | 0.45 | 0.89 |
| t10 | 0.60 | 0.51 | 0.90 |
| t11 | 0.50 | 0.41 | 0.89 |
| t12 | 0.28 | 0.15 | 0.97 |
| t13 | 0.48 | 0.46 | 0.87 |
| t14 | 0.65 | 0.76 | 0.90 |
| t15 | 0.63 | 0.73 | 0.83 |
| t16 | 0.48 | 0.41 | 0.88 |
| t17 | 0.45 | 0.44 | 0.89 |
| t18 | 0.39 | 0.39 | 0.91 |

MAE - Mean Average Error, MSE - Mean Square Error

The results of the experiment relevant for RQ4 showed that obtained values correlate with the teachers' grades. Although the Spearman's R correlation test result indicates very strong association between predicted and teachers' grades, calculated MAE and MSE per student, as well as MAE, MSE and R-squared per teacher differ. However, the results show that there is potential for using obtained values for the grading. This is important because is it difficult for the teacher to evaluate the quantity and continuity of student/group contributions based on the raw data, especially in the case when assessing various categories of contributions within the same e-tivity.

## VI. Conclusion

In this paper we have presented a quantitative approach to student and group activity level assessment in an e-learning 2.0 environment that serve as basis to raise awareness and provide recommendations during the learning process. The results show that the proposed approach can be used to estimate the student and the group activity level in the context of collaborative e-tivities realized using Web 2.0 tools. Categorization of activity traces provides a mechanism for the evaluation of different contributions, while the quantitative analysis of activity traces and evidence certainty factors calculation enable estimation in relation to other participants. Results also show that the approach can support teachers when deciding on number of points regarding quantitative aspect of students' participation.

Further work regarding the proposed approach is needed to assure interventions in case of fake student behavior and improve the presentation of calculated data to students/teacher in terms of visualization. It will also include the efforts to model the qualitative aspects of student's contributions with the potential to support formative and summative assessment, and enable additional adaptive interventions during collaborative e-tivities.

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