An Analysis of Factors Affecting Automatic Assessment based on Teacher-mediated Peer Evaluation
The Case of OpenAnswer

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Abstract: In this paper we experimentally investigate the influence of several factors on the final performance of an automatic grade prediction system based on teacher-mediated peer assessment. Experiments are carried out by OpenAnswer, a system designed for peer assessment of open-ended questions. It exploits a Bayesian Network to model the students' learning state and the propagation of information injected in the system by peer grades and by a (partial) grading from the teacher. The relevant variables are characterized by a probability distribution (PD) of their discrete values. We aim at analysing the influence of the initial set up of the PD of these variables on the ability of the system to predict a reliable grade for answers not yet graded by the teacher. We investigate here the influence of the initial choice of the PD for the student's knowledge (K), especially when we have no information on the class proficiency on the examined skills, and of the PD of the correctness of student's answers, conditioned by her knowledge, P(C|K). The latter is expressed through different Conditional Probability Tables (CPTs), in turn, to identify the one allowing to achieve the best final results. Moreover we test different strategies to map the final PD for the correctness (C) of an answer, namely the grade that will be returned to the student, onto a single discrete value.

1 INTRODUCTION

Peer assessment is widely deemed to be a useful exercise to challenge as well as improve one's understanding of a topic but also to achieve higher *metacognitive* abilities. Actually, according to Bloom's taxonomy of educational objectives in the cognitive domain (Bloom *et al*., 1956), learner's abilities increase when passing from pure knowledge (the ability to remember a topic is considered at the lower level), to comprehension, application, analysis, evaluation and finally synthesis. In (Anderson *et al.,* 2000) a revised version of the taxonomy is proposed, where *remember*, *understand* and *apply* lay at increasing levels, while *analyse*, *evaluate* and *create* lay at the same top level. In any case, the ability to evaluate is considered a higher one. It is a *metacognitive* skill going beyond the proficiency in a single topic, though requiring it. As a matter of fact, as discussed by Metcalfe and Shimamura (1994), metacognitive activities require not only knowing but also knowing about knowing. The accepted definition of metacognition refers to higher order thinking, entailing the ability to exercise an active control over the cognitive processes underlying learning. Planning strategies and schedules to carry out a learning task, monitoring one's and others' comprehension of a topic and the progress towards the completion of a task, and being aware of how to apply newly acquired concepts and rules, all play a critical role in successful learning. Therefore, besides exercising cognitive skills, also metacognitive ones should be cared for in educational planning. Peer assessment can be exploited to this aim. The framework implemented through the OpenAnswer system (Sterbini and Temperini, 2012, 2013a, 2013b) adopted for the experiments presented in this paper allows (semi-)automated grading of open answers through peer assessment, with the further goal of relieving the teacher from part of the burden of grading the complete set of answers. As a matter of fact, while this kind of exercise provides a much more reliable evaluation of students' proficiency with respect to, e.g., multiple-choice tests (Palmer

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and Richardson, 2003), they are also much more demanding for the teacher too since they require a longer revision activity. Of course, the condition for the system to be useful is to provide reliable outcomes, and we are investigating several factors that could affect them. During an OpenAnswer assessment session, each student is requested to grade some (e.g., 3) of her/his peers' answers. The validity of results of peer evaluation is enforced by requiring that a subset of answers (chosen according to some relevant criterion which will be discussed in the following) is further graded by the teacher. Information provided by peers' and teacher's assessments is fed and propagated within a Bayesian Network (BN). In such network the students are modelled by their Knowledge level on the topic (*K*), and by the correctness of their evaluations, denoted as Judgment (*J*). In the network, the answers of a single student have an estimated Correctness (*C*). Such value can be updated by evidence propagation. When a student marks an answer by a peer, a corresponding Grade (*G*) is injected into the network, and propagates its effects depending on both *J* of the grading student and on current estimation of *C* of the peer answer. Variables *C* and *J* are assumed to be conditioned by *K* ($C|K$ and $J|K$), therefore for each of them we have a Conditional Probability Table (CPT). In this process, students can both understand how the grading process should work, by matching the grades they assigned with final ones (possibly by the teacher, or inferred by the system through the BN), and learn from smarter peers how to improve their results (Sadler and Good, 2006). Providing to the students the final values of their own *K* and *J* returned by the system, besides the pure exercise grade, can spur further metacognitive awareness.

In the present work we first use traditional assessment (done by the teacher in the whole, and being our ground truth) to systematically evaluate and compare with it the grading accuracy achievable by different policies to use our teacher-mediated peer assessment. These strategies range from pure manual peer assessment to peer assessment propagated by OpenAnswer without teacher's grading, to complete exploitation of OpenAnswer potentialities with peer assessment complemented by teacher's (partial) grading in OpenAnswer, with different strategies for the choice of next answer to grade and for termination (no further grading is required from the teacher). In this respect, we introduce new strategies for the choice of the next answer, namely *maxInfoGain*, *maxStrangeness*, and *maxTotalEntropy*, which will be detailed in the following. We evaluate the influence of some preliminary choices on system performance. More important, we want to show how the work by the teacher in our framework can improve the pure peer assessment accuracy. In this context we investigate the effect of different choices for the initial distribution of K values (for each student) on system evaluation performances, especially when no or little knowledge is available on specific students' skills on the topic at hand. We evaluated different choices for the initial CPT of $C|K$, that then evolves to a final value during the peer assessment/teacher grading. Then we compared different strategies to map the grade distribution (*C*), achieved by each student, onto a single final grade.

2 RELATED WORK

The automatic analysis of open answers is a powerful means to manage assessment in education, also known as *knowledge tracing* (Anderson *et al*., 1995). It is met, though, in other fields, such as in a context of marketing applications, where techniques of data mining and natural language processing are used to extract customer opinions and synthesize products reputation (Yamanishi and Li, 2002). In (Jackson and Trochim, 2002) concept mapping and *coding schemes* are used with the same goal. The (semi-)automatic assessment of open-answers proposed in (Castellanos-Nieves *et al.*, 2011) relies on ontologies and semantic web technologies. The ontology models the knowledge domain related to the questions, and also aspects of the overall educational process. In (El-Kechaï *et al.*, 2011) open answers are examined to identify and treat students misconceptions which hinder learning

Peer-assessment is the activity in which a learner, or a group of learners, assesses the product of other learners (the peers) meanwhile engaging in a notoriously high cognitive level activity (Bloom *et al*., 1956). Peer-assessment can be used to pursue both *formative* and *summative* aims (Topping, 1998): in the first case the aim is to allow the learner to appreciate her cognitive situation (such as level of knowledge, or lacks therein) and monitor her progress. In the second case not all the available information might reach the learner, and the aim is to evaluation and possible support to the selection of remedial activities.

Li *et al.* (2010) states that a relationships does exist between the quality of the peers feedback, on a learner's job, and the quality of the final project submitted by the learner. A comprehensive study of peer assessment in a prototype educational application is in Chung *et al.* (2011).

The OpenAnswer system relies on the evaluation of answers coming from peer-assessment, and on the student modelling managed by Bayesian Networks. Another machine learning approach to student modelling is in (Conati *et al.*, 2002), where Bayesian Network techniques are used to support learner's modelling in an Intelligent Tutoring System (ITS). The modelling is devised to support activities relevant in an ITS: knowledge assessment, plan recognition and prediction, the last two deemed to see what intentions are behind a learner's choice, and what following choices might be, during the phase of problem solving.

In OpenAnswer the peer is presented with a set of assessing criteria, to refer to while marking; the criteria are defined by the teacher, and are supposed to be adhered to by the teacher, during her grading too. In our experience too many criteria might result cumbersome for the peers. We have not investigated, though, on this aspect. In literature the specificity of "scoring criteria" has been identified as an important factor against the problem of having assessors that limit the range of their marks to a subset (typically in the high end) of the scale; in this case the problem is twofold, involving both peers leniency and shrinking of the marking scale (Miller, 2003).

An aspect of research in peer-assessment regards the number of peer-evaluations that a same job should undergo during the peer-evaluation process. In OpenAnswer this is configurable, with default to 3. In literature it is found that more feedbacks on the same job make the peer performing more complex revisions on her product, ending up with a better result (Cho and MacArthur, 2010).

3 OpenAnswer SYSTEM

The intended use of OpenAnswer system is to support semi-automatic grading of answers to open-ended questions (*open answers*) through peer assessment. From one side, it can be used by the teacher to spur students' evaluation metacognitive ability, and therefore to also evaluate their performance in assessing the answers of their peers, thus getting further information on their deep understanding of topics. From the other side, it may underlie strategies to limit the amount of teacher's grading effort. Many proposed systems are developed along the first line. We pursue both. After all, automatic grading techniques relying exclusively on peer assessment are still not reliable enough. OpenAnswer (Sterbini and Temperini, 2012, 2013a, 2013b), as well as similar previous work (Sterbini and Temperini, 2009), rather adopts a mixed approach, to pursue both goals at the same time. In order to enforce/emend the results of peer evaluation, and therefore increase the reliability of final grades, the teacher is required to assess some part of the answers, whose number and identification depends on the chosen corresponding strategies that will be presented in the following. In this way the teacher's grading workload will be reduced, therefore encouraging a more frequent use of an educational strategy entailing open answer tests and peer assessment, while students will receive both the grading of their answers and be able to compare their peer grading with the correct one. As further detailed below, the system suggests to the teacher the order of answers to manually grade, according to a selection strategy chosen in advance among a number of available ones. Manual grading can stop when some pre-defined termination criterion is met. Even in this case, a number of criteria are available. After the termination criterion is met, the system automatically completes the grading task for the remaining answers using the correctness information collected so far, together with the results of the peer grading. The OpenAnswer approach relies on a simple Bayesian network model. The individual student model is represented by a Bayesian network. The variables defining the model include an assumed value for the learner's state of knowledge on the exercise topic (K), and the ability to judge (J) answers given by peers on the same topic. Actually, as it is quite natural, we assume that the value of J is conditioned by the value of K. These variables are exploited in the system state evolution and affect the way information is weighted while propagated. For each peer assessment session, the individual student networks are interconnected depending on the current sets of answers that each student receives to grade. Therefore, different sessions may entail different interconnection patterns. Each answer is characterized by its correctness (C), measuring the student ability to provide a correct solution, and by the grades (G) assigned by the peers to it. C is a variable depending on the student K value and is characterized by a conditional PD, that reduces to a single grade once the answer is manually graded by the teacher. All variables are characterized by a probability distribution (PD) of discrete values that follows the same convention of grading. In our case, depending on the datasets used as testbed, this entails 6 (from A to F) or 5 (A, B, C, D, F) values, with F=Fail.

It is worth underlying that, according to Bloom's taxonomy and building on results presented in (De Marsico *et al.*, 2015), we chose a PD which, for each value of *J|K=k*, has its maximum on *k-1*. This is supported by the assumption, confirmed by evidence, that judging the work of a peer is more engaging that carrying out the same work. In this work we want to assess if this choice is also suitable for *P(C|K)*. To this aim we investigate the influence of different definitions for *P(C|K)* on system outcome reliability.

C and *G* control evidence propagation according to the possible matching between teacher's and peer assessments. In particular, the *J* of a student is connected to the *C*s corresponding to the evaluated peer answers through the assigned grades *G*. The resulting compound network is continuously updated. Figure 1 shows an example BN fragment for a student that graded three peers. Evidence propagation happens in two phases. The first one is only based on peer assessment grades (*G*). Afterwards, when the teacher starts grading, the grades provided affect the *C* variables of corresponding answers (they become fixed values, i.e. the conditional PD concentrates on a single value), therefore affecting *J* values of grading peers through the *G*s that they assigned to the same answers. In turn, this indirectly affects *J* and *K* variables of the student author of the answer, and indirectly the *J* and *K* values of grading peers.

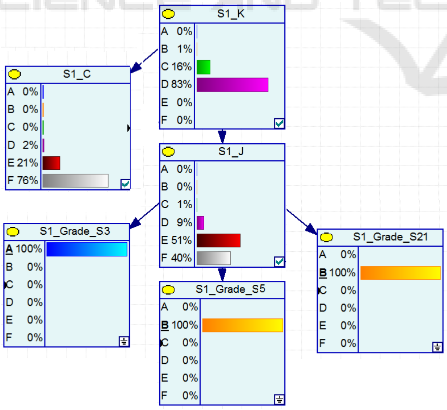


Figure 1: An example fragment of Bayesian Network in OpenAnswer: student S1 grades the answers of students S3, S5 and S21, and notwithstanding the most probable value of D for K, presents a current most probable grade F for his/her answer.

During the following manual grading phase, the system supports the teacher by suggesting the next "best" answer to grade according to one of the selection criteria detailed below, and by propagating in the network the added information provided by the teacher's grade. After each evidence propagation step, the teacher grading step is iterated until a termination condition is met. In practice, the latter states that new information from additional teacher's grades would be less decisive. When the teacher stops grading after a sufficient number of answers, the information collected so far allows to automatically grade those answers that were not directly graded by the teacher. In practice, grades not directly given by the teacher are inferred according to the current probability distribution associated to the *C* values. Of course, it is necessary to devise also a suitable mapping strategy from PDs to single values to return to students.

The possible system strategies to suggest the next answer to grade are:

- *max_wrong*: the system suggests to grade the most probably incorrect answer, i.e. the one with highest probability of having *C='F'*;
- max_*entropy*: the system suggests to grade the answer presenting the highest entropy (the answer the system *knows* less about, or about which has less information for inference); the entropy of an answer is the entropy of the corresponding *C* variable;
- *maxInfoGain*: the system chooses the answer that guarantees the greater assured information variation; the latter is the minimum variation of total entropy of the network that is produced by each of the possible grades that the teacher might assign to a certain answer, by propagating the grade choice in the network; the total entropy of the network is the sum of entropies computed for all K, J and C variables of all students in the BN; of course this strategy is the slowest one, but no real time outcome is required;
- *maxStrangeness:* the system chooses the answer with the greater *strangeness*; *strangeness* is the absolute value of the difference between *J* and *C* (after mapping their current respective PDs as computed by the network into single values); this is to capture the two peculiar cases of a student with high *C* but low *J* (good knowledge but low judgment ability) and vice versa;
- *maxTotalEntropy*: the system chooses the answer by the student with maximum *total entropy*, with *total entropy* of a student being the sum of the entropies of the associated C, J and K variables;
- *random*: the next answer to grade is chosen at random; this strategy is mostly used for testing purposes, as it should provide a comparison with totally random choices, and indirectly information

on the effectiveness of chosen alternatives; it is not used in the present work;

The termination criterion can be chosen among the following:

- *none*: no answer at all is graded by the teacher, therefore this corresponds to “pure” peer assessment yet with the evidence propagation provided by OpenAnswer;
- *no_wrong*: no more ungraded answers exist which would be automatically graded as wrong (C='*F*') once the PD of C is mapped onto a grade;
- *no_wrong2:* for all remaining answers *P(C=’F’) ≤1/2*;
- *no_wrong3:* for all remaining answers *P(C=’F’) ≤1/3*;
- *no_flip(N)*: the automatically computed grades remained stable in the last N correction steps.

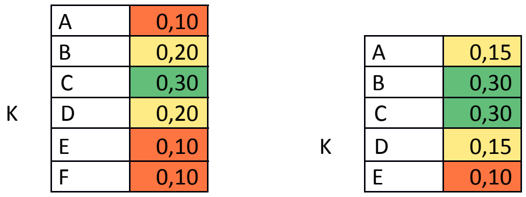
In general, *max_wrong* is best associated with *no_wrong<p>* and *max_entropy* with *no_flip(N)*, while *random* can be associated with both the termination criteria.

4 ASPECTS INVESTIGATED IN THE EXPERIMENTS

In the present work, we explored different evaluation settings for OpenAnswer system. First, we matched grading accuracy achievable through peer assessment against traditional assessment (completely by the teacher, our ground truth) in different settings: 1) pure peer assessment (without OpenAnswer system), 2) peer assessment with OpenAnswer without teacher's contribution (propagation of peer grades through the Bayesian network in OpenAnswer, without any grading by the teacher, i.e. termination=none), 3) peer assessment complemented by teacher's (partial) grading in OpenAnswer, with different policies for the choice of next answer to grade and for termination (no further grading is required from the teacher). To this respect, we introduce new strategies for the choice of the next answer, namely *maxInfoGain*, *maxStrangeness*, and *maxTotalEntropy*, described in the previous section. Our main goal is to evaluate the influence of some preliminary choices on system performance, i.e., on the quality of assessment, on its reliability (rate of grades correctly inferred), and on the work requested by the teacher.

In this context we investigated also the effect of different choices for the initial distribution of K values (for each student) on system evaluation performances. We have two possible alternatives. The first one can only be used in experimental settings, and entails an ex-post knowledge of the group of students and their learning state on the specific topic being assessed. The assumption is that having such knowledge can improve the quality of information propagation in the BN. In this case we exploit two sub-choices. The first, more relaxed one is to assume for all students the same probability distribution for K, which is equal to the distribution obtained for the manual exercise grading (performed completely by the teacher) that is used as ground truth. This is reported by columns labelled as **TgrDist** (Teacher’s Grade Distribution) in the tables reporting experimental results. It is worth underlining that this choice can also realistically model cases, that we do not consider here, when we can inherit and exploit the distribution of knowledge of the class obtained in previous assessment sessions on a similar topic. The second entails assigning to each student with probability=1 the level of knowledge corresponding to the grade achieved, again obtained from teacher’s grading. This is reported by columns labelled as **Tgrade** (Teacher’s Grades) in the tables reporting experimental results. The Tgrade distribution is the less realistic one and can be considered as an upper bound, as we will discuss in more detail in the following.

The second situation is the realistic one, and entails ex-ante attempts to model students in a starting setting, where no or little knowledge is available on specific students’ skills on the topic at hand. In this case we have further two sub-choices, namely: to assume for each student an equal probability for all K levels, reported by columns labelled as **flat** in the tables reporting experimental results, or to apply to all students a same, synthetic and “reasonable” PD for *K,* reported by columns labelled as **synthetic**. The synthetic PDs for K for 6 or 5 grade values are shown if Figure 2.



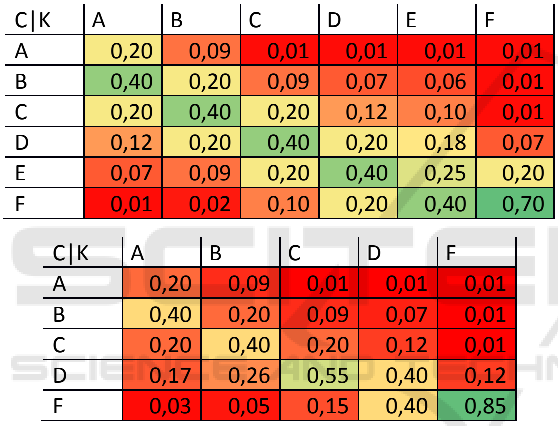
K	A	0,10
	B	0,20
	C	0,30
	D	0,20
	E	0,10
	F	0,10

K	A	0,15
	B	0,30
	C	0,30
	D	0,15
	E	0,10

Figure 2: Synthetic PDs, stating initial values of K, in the cases of 6-valued and 5-valued scale for the value of K.

We use the “artificial” setting, in particular Tgrade, to evaluate an upper bound to achievable results. Once we identify the combination <strategy, termination> achieving the best results, we can observe which is the best realistic distribution for K values to adopt with this combination.

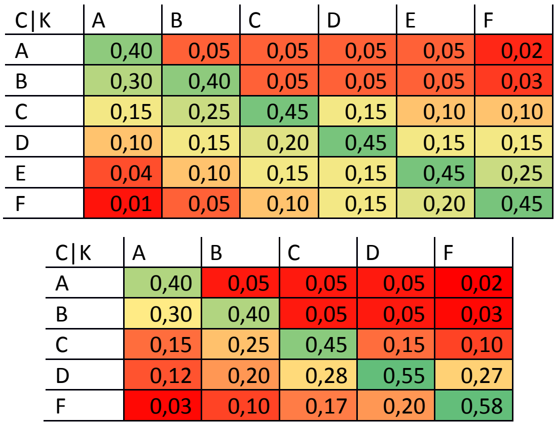
As a further element that can affect final effectiveness of OpenAnswer assessment, we tested different Conditional Probability Tables (CPTs) for the level of correctness P(*C*|*K*). We started from the same CPT as for *J*|*K*, which entails a distribution that for each value of *C*|*K=k* has its maximum on *k-1*. We show the corresponding CPTs (labelled as **CPT1**) (in Figure 3 the two cases of 6-valued and 5-valued grading scale are shown). This CPT differs from the others for both the choice of the value of *C* with maximum probability for each value of *K*, and for the fraction of probability assigned to such value. It is worth underlining that at the moment this is the same CPT that we use in all experiments for *P(J|K)*. In the future we plan to test different choices for *P(J|K)* too.



C|K	A	B	C	D	E	F
A	0,20	0,09	0,01	0,01	0,01	0,01
B	0,40	0,20	0,09	0,07	0,06	0,01
C	0,20	0,40	0,20	0,12	0,10	0,01
D	0,12	0,20	0,40	0,20	0,18	0,07
E	0,07	0,09	0,20	0,40	0,25	0,20
F	0,01	0,02	0,10	0,20	0,40	0,70

C|K	A	B	C	D	F
A	0,20	0,09	0,01	0,01	0,01
B	0,40	0,20	0,09	0,07	0,01
C	0,20	0,40	0,20	0,12	0,01
D	0,17	0,26	0,55	0,40	0,12
F	0,03	0,05	0,15	0,40	0,85

Figure 3: CPT1: for each k the probability distribution of P(C|K=k) in column k, has its maximum on row C=k-1 (the upper table shows the values for the 6-valued grading scale; the lower table is related to the 5-valued scale).

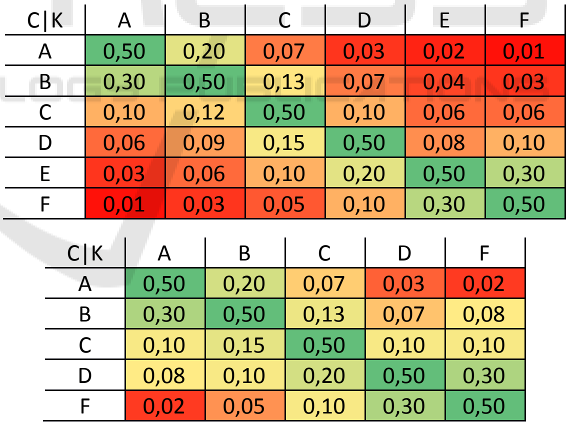


C|K	A	B	C	D	E	F
A	0,40	0,05	0,05	0,05	0,05	0,02
B	0,30	0,40	0,05	0,05	0,05	0,03
C	0,15	0,25	0,45	0,15	0,10	0,10
D	0,10	0,15	0,20	0,45	0,15	0,15
E	0,04	0,10	0,15	0,15	0,45	0,25
F	0,01	0,05	0,10	0,15	0,20	0,45

C|K	A	B	C	D	F
A	0,40	0,05	0,05	0,05	0,02
B	0,30	0,40	0,05	0,05	0,03
C	0,15	0,25	0,45	0,15	0,10
D	0,12	0,20	0,28	0,55	0,27
F	0,03	0,10	0,17	0,20	0,58

Figure 4: Second tested CPT2: for each value K=k we devised a “reasonable” distribution for C values. Again the two cases of 6- and 5-valued grading scale are shown.

As a second alternative we tested a ”reasonable” distribution of C values for each value *K=k*. Figure 4 shows the corresponding CPTs (**CPT2**). Then we tested two other CPTs for C that not only concentrate the highest probability on *c=k*, but also assume such probability *P(C=k|K=k)=0.5*. In both cases, half conditional probability is concentrated on the same value the student achieves for *K*, while the remaining 0.5 is divided according to some criteria among the other grades. And in both cases we assumed a higher probability to achieve a correctness value which is lower than K than a higher one. For the first case, we created the conditional probability distributions *P(C|K='A')* and *P(C|K='F'),* (corresponding to the first and last column in the CPT), which represent extreme cases, establishing some “reasonable” relations among such probabilities. As for the other columns, we assumed 2/5 of the remaining probability (total 0.20) to achieve a higher grade, and 3/5 (total 0.30) to achieve a lower one. Given *m* the number of higher (lower) grades to handle, we then computed $SLICES = \sum_{i=1}^{m} 1$, and assigned to the less probable grade $0.20 \times SLICES$, to the second less probable the grade $0.20 \times 2 \times SLICES$, and so on (respectively, $0.20 \times SLICES$, $0.20 \times 2 \times SLICES$, and so on). Figure 4 shows the resulting CPTs.



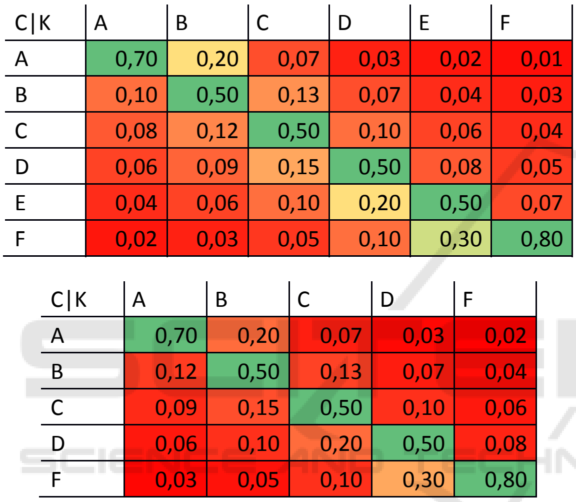
C|K	A	B	C	D	E	F
A	0,50	0,20	0,07	0,03	0,02	0,01
B	0,30	0,50	0,13	0,07	0,04	0,03
C	0,10	0,12	0,50	0,10	0,06	0,06
D	0,06	0,09	0,15	0,50	0,08	0,10
E	0,03	0,06	0,10	0,20	0,50	0,30
F	0,01	0,03	0,05	0,10	0,30	0,50

C|K	A	B	C	D	F
A	0,50	0,20	0,07	0,03	0,02
B	0,30	0,50	0,13	0,07	0,08
C	0,10	0,15	0,50	0,10	0,10
D	0,08	0,10	0,20	0,50	0,30
F	0,02	0,05	0,10	0,30	0,50

Figure 5: CPT3, 6-valued (up) and 5-valued grading scale): half probability is concentrated on C=k|K=k.

The last CPT tested follows the rules above also for the first and last columns (*K='A'* and *K='F'*), except that the amount of probability which is not applicable (the probability to increase the grade for *K='A'* or decrease it for *K='F'*) is summed to *P(C=k|K=k).*

We finally evaluated different strategies to map back the correctness distribution (*C*) achieved by each student at the end of the evaluation session into a single grade (parameter P2VAL - *prob2value* in the tables below). We explored different solutions: 1) take the centre of the interval corresponding to the grade with highest probability (label **max1P** in the experiment tables); 2) take the weighted and normalized sum of the two grades in the distribution with the highest probabilities (label **max2P**), where weights are the achieved probabilities; 3) take the weighted and normalized sum of the three grades in the distribution with the highest probabilities (label **max3P**); 4) take the weighted and normalized sum of all grades in the distribution (*weightedSum* - **wSum** in the tables below); 5) take the weighted sum of the most probable values, till to reach 75% of accumulated probability (label **best75%**).



C|K	A	B	C	D	E	F
A	0,70	0,20	0,07	0,03	0,02	0,01
B	0,10	0,50	0,13	0,07	0,04	0,03
C	0,08	0,12	0,50	0,10	0,06	0,04
D	0,06	0,09	0,15	0,50	0,08	0,05
E	0,04	0,06	0,10	0,20	0,50	0,07
F	0,02	0,03	0,05	0,10	0,30	0,80

C|K	A	B	C	D	F
A	0,70	0,20	0,07	0,03	0,02
B	0,12	0,50	0,13	0,07	0,04
C	0,09	0,15	0,50	0,10	0,06
D	0,06	0,10	0,20	0,50	0,08
F	0,03	0,05	0,10	0,30	0,80

Figure 6: CPT4: half probability is concentrated on C=k|K=k plus, in first and last columns, the total probability of increasing or decreasing the grade.

5 EXPERIMENTAL RESULTS

The datasets we exploited for experiments are collections of exercises with their corresponding peer assessment data. In addition, each peer assessment session is integrated by the teacher complete grading: it is used as ground truth to evaluate the reliability of the semi-automatic grading results returned by OpenAnswer. Datasets come from different educational contexts, namely University or High School, and exercises deal with different topics, from both scientific and social sciences courses.

Table 1 reports the composition of each collection.

Table 1: The composition of the used benchmark data.

Dataset	Level	Topic	Groups	Students
A-6-1	Univ.	4 exercises on multi-level cache systems	2	7 to 15
M-6-1	Univ.	3 exercises on C programming	2	9 to 13
I-6-1	High School	1 physics exercise	2	14 and 12
A2-5-4	Univ.	1 essay on social tools	5	12

Near to each collection label we report the number of values used for grade/levels, that are used in turn to model the discrete Bayesian variables, and the number of teachers involved. When more teachers graded the same exercise, we run an independent simulation for each of them, using the same data from students, with different teacher grading. We first report the average performance of pure peer assessment over the different sessions on the different datasets, i.e., the accuracy of students' grading w.r.t. the ground truth of teachers' grading.

Table 2 reports the average percentage of correct (i.e. equal to teacher's) peer grades (OK/TOTAL) and of grades within 1 mark (IN1/TOTAL) from the teacher grade. Regarding rows labelled as "A2 avg" and "A2 median" in Table 2, we remind that in dataset A2 the students' answers were graded by 4 different teachers. In the first row in Table 2, the grade set of each teacher is considered as a separate experiment, and the average results of the 4 are reported, while in "A2 avg" and "A2 median" we considered a single experiment using as grades either the average or the median grades over the four teachers, respectively.

Table 2: OK/TOTAL represents the average percentage over different datasets of peers' grades equal to teacher's grades, while IN1/TOTAL represents the average percentage over different datasets of peers' grades within one grade from teacher's (still considered acceptable).

DATASET	DOMAIN	OK/TOTAL	IN1/TOTAL
A2	5	47.13%	91.57%
A2 avg	5	58.82%	94.12%
A2 median	5	58.82%	95.59%
A	6	37.84%	67.57%
I	6	57.69%	96.15%
M	6	27.94%	72.06%
A+M+I+A2 (weighted)	6 and 5	42.72%	84.16%

The test provides an overall average rate of correct grades of 42.72%, while if we admit a difference of ±1 grade we get 84.16%. The overall average is weighted with respect to the number of experiments in each dataset. It is interesting to notice that when using “A2 avg” and “A2 median” as ground truth, better performance are obtained. This seems to suggest that the difference in grading criteria among different teachers has a clear influence on the evaluation of the results of peer assessment. In practice, the students’ assessment is closer to the assessment carried out by an “average” or “median” teacher, so that individual episodic differences are smoothed.

In the experiments presented in the following we do not enter anymore into details regarding the single collections, but rather discuss the obtained average results over all simulations. As a first step, we compare the above “correctness” rates with those obtained by having OpenAnswer just propagate peer grades as they are across the BN (i.e., we select termination = *none*). The results show how different initial settings for *P(K)* and *P(C|K)* and different mapping rules from *P(C|K)* (a distribution) to the final grade (a single value) can influence the reliability of outcomes. Table 3 shows the obtained results. The first observation is that, among the Conditional Probability Tables (CPTs) tested in our experiments, the best one is the one modelled manually by an experienced teacher (**CPT2**). In fact, using the other CPTs, also the results obtained adding some amount of teacher grading achieved a lower accuracy. We will therefore continue our presentation of experimental results only referring to that CPT. It is further interesting to notice that this CPT causes a fair behaviour of the BN. When no information is provided about the class, the network is quite neutral (the results are very close to those obtained by pure peer assessment). On the contrary, when some amount of knowledge about the class learning state is added by exploiting the teacher’s grade distribution from the ground truth (**TgrDist**), a significant improvement is obtained using the BN. Of course the best result is obtained by using the true teacher’s grades as initial knowledge about the class (**Tgrade)**, entailing to know the exact grade in advance (as noticed, this is an upper bound). In the following, we will compare the more realistic **flat** (no knowledge at all on the class) and **TgrDist** (past knowledge) distributions. As a further observation, the weighted sum (**wSum**) rule to map a grade distribution onto a final value gives the best results in most cases even in the following experiments. Therefore, we will always report results obtained by this strategy.

Results in Table 3 confirm our hypothesis that pure peer assessment without OpenAnswer information propagation can be considered as a lower bound of the achievable accuracy (agreement with teacher’s grades). As a matter of fact, using a BN propagation, based on a suitable starting assumption/knowledge for the *P(K)* of the class, provides some improvements on the accuracy, even without any teacher’s grading. We continue our experimentation by searching for an upper bound of the achievable accuracy. To this aim, we assume a fictitious initial exact knowledge of the outcome (**Tgrade**), i.e., a distribution of values for *K* such that, for each student, *P(K)=1* on the grade actually achieved by the student. Our next hypothesis is that the full use of OpenAnswer with such exact knowledge about the class proficiency should represent the searched upper bound. It is worth underlining that, since grades are partly inferred anyway, a 100% accuracy will not be achieved in this case neither. As a final hypothesis, we want to verify that full use of OpenAnswer with a more realistic set-up of *P(K)* provides results that are between BN propagation without teacher’s grading and the use of teacher’s grading with the best possible knowledge (actually, knowing results in advance). Of course this would not necessarily hold for all possible combinations of the CPT for *C*|*K*, the initial setting for *P(K)*, the mapping from distribution to grade, and the strategy next answer choice/termination: our goal is just to find out the best such combinations.

Table 4 and Table 5 present the results that we obtained for the best candidates identified from Table 3 (**CPT2, wSum**) with different next answer choice/termination strategies for **flat** and **TgrDist** initial distributions for *P(K),* respectively.

In Tables 4 and 5 the groups of rows labelled **L/TOTAL** report, for each choice strategy for the next answer to grade and for each termination condition, the percentage of questions manually graded by the teacher (a measure of the teacher’s effort). The groups of rows labelled as **(OK+L)/TOTAL** report the total percentage of answers correctly graded (either by the teacher or by the system through peer assessment), while groups **(IN1+L)/TOTAL** report a similar value for answers finally graded by a value that is ±1 the correct grade. We remind that correct grades are available as ground truth for experimental evaluation. In both Table 4 and Table 5, the column **none** (for termination condition) reports the same values for all strategies, since it corresponds to the situation where the teacher does not correct any answer, and therefore neither next choice strategies nor

Table 3: Results obtained for pure peer assessment supported by BN propagation, using different CPTs, different initial settings for P(K) and different procedures to map a probability distribution onto a single vote; no teacher grading is entailed.

		TERMINATION=none (no teacher correction)											
		Average - OK/TOTAL						**Average - IN1/TOTAL**					
	P (K)	**best75**	**max1P**	**max2P**	**max3P**	**wSum**	**Increment**	**best75**	**max1P**	**max2P**	**max3P**	**wSum**	**Increment**
CPT 1	**flat**	39,01%	38,62%	36,96%	39,72	**39,44**	-3,00%	**81,44%**	81,25%	80,56	80,86	81,22	-2,72%
	synthetic	38,79%	36,56%	35,51%	**39,90**	39,30	-2,83%	82,76%	80,44%	79,66	**83,25**	81,68	-0,91%
	Tgrade	39,76%	29,80%	28,60%	**46,23**	40,86	3,50%	92,83%	**94,74%**	92,72	90,83	91,29	10,58%
	TgrDist	39,60%	37,34%	37,35%	40,72	**42,01**	-0,72%	**85,81%**	82,32%	81,00	83,65	84,41	**1,65%**
CPT 2	**flat**	40,30%	37,85%	36,18%	40,24	**42,12**	-0,60%	81,16%	81,02%	80,73	84,12	**85,45**	1,29%
	synthetic	40,68%	40,34%	39,56%	40,40	**41,85**	-0,87%	82,17%	80,83%	81,09	84,66	**86,04**	1,88%
	Tgrade	64,03%	**82,96%**	73,83%	55,04	58,28	40,23%	93,72%	93,26%	92,48	**94,21**	93,94	10,05%
	TgrDist	43,67%	**48,44%**	46,04%	44,63	45,60	**5,72%**	85,71%	84,02%	83,72	86,89	**87,05**	**2,89%**
CPT 3	**flat**	38,56%	36,67%	35,75%	40,33	**40,87**	-1,85%	80,94%	81,03%	81,12	83,61	**84,43**	0,27%
	synthetic	37,90%	37,22%	35,76%	38,15	**42,50**	-0,23%	80,90%	82,06%	81,59	82,59	**84,19**	0,03%
	Tgrade	70,39%	**81,10%**	72,24%	63,07	66,51	38,38%	**94,94%**	94,61%	94,81	95,43	94,54	11,27%
	TgrDist	40,71%	43,12%	41,59%	40,37	**43,32**	0,60%	82,86%	84,29%	83,83	84,90	**85,69**	**1,53%**
CPT 4	**flat**	37,10%	32,02%	33,52%	37,12	**39,34**	-3,38%	79,92%	72,38%	76,32	81,41	**83,44**	-0,72%
	synthetic	36,68%	35,24%	35,52%	37,06	**41,09**	-1,63%	79,43%	77,68%	78,27	82,44	**84,21**	0,05%
	Tgrade	72,25%	**81,48%**	74,37%	67,80	71,22	38,75%	95,41%	94,34%	95,01	**95,90**	94,77	11,74%
	TgrDist	39,10%	42,10%	39,76%	39,46	**43,50**	0,78%	81,61%	80,28%	81,24	83,64	**84,22**	0,06%

termination conditions are involved. The value only changes when passing from **OK** (correctly inferred) to **IN1** (correctly inferred plus those inferred at a distance of ±1 grade). For the same reason, the rows corresponding to **L/TOTAL** are empty and (**OK+L)/TOTAL** in this column has always a value equal to **OK/TOTAL.** Finally notice that values **OK/TOTAL** and **IN1/TOTAL** under column **none** report the same values in the corresponding settings as reported in Table 3.

In Table 4 it is possible to notice that inferred grades alone do not reach the accuracy of pure peer evaluation with propagation (column **none**).

However, if we add some teacher's work, we can observe a significant improvement in accuracy, even though this is obtained at the expense of more teacher's effort (see discussion in the next section). Using MaxTotalEntropy with noFlip3, we reach 80.63% (OK+L)/TOTAL and 95.32% for (IN1+L)/TOTAL at the expense of about 68% answers manually graded. It is also possible to consider, by comparing values in the different combinations, that the earliest the system stops (e.g., noFlip1 vs. noFlip3) the lower the teacher's work but the lower the accuracy too. Though these results seem not brilliant, it is to consider that Table 4 refers to a situation where we assume no knowledge about student's learning state, therefore we start from an initial setting for P(K) where all values are equally probable. Table 5 demonstrates that a certain amount of preliminary knowledge of the class learning achievements can improve accuracy results.

6 DISCUSSION

A first observation is in that the better results obtained using CPTs, for the conditional probability P(C|K), seem to suggest that simple mathematical relations cannot satisfactorily model the anticipation of possible correctness of student responses, just basing on their level of knowledge on a topic.

Then, the better results obtained with "manually" produced CPTs seem to testify that the experience gained by a teacher is of paramount importance in carrying out such kind of modelling.

As a further consideration, we can discuss the often better accuracy of results, in terms of (OK+L)/TOTAL, obtained by the random strategy to choose the next answer to grade. This is not the contradiction it might appear to be: using this strategy (that is, avoiding to use any strategy), we cannot neither choose nor anticipate in any way the amount of information that the next grading will allow to propagate in the BN. So the teacher will grade more answers (corresponding to a higher value for L/TOTAL) in order to feed the automatic inference with sufficient information. In other words, the final accuracy will be higher because, with a random choice of the next answer to grade,

Table 4: Results obtained by adding teacher's grade with P(K)=flat (no assumption on class knowledge) and for probability to value (label P2VAL) = wSum, using CPT2; teacher grading is carried out using different strategies to choose the next answer to grade, and different termination conditions.

P(K)=flat	P2VAL=wSum	TERMINATION						
Data	**STRATEGY**	**noFlip1**	**noFlip2**	**noFlip3**	**none**	**noWrong**	**noWrong2**	**noWrong3**
Average - OK/TOTAL	**maxEntropy**	35,97%	24,85%	17,34%	42,12%	31,08%	31,59%	31,08%
	maxInfoGain	32,40%	26,24%	18,08%	42,12%	31,77%	32,27%	31,45%
	maxStrangeness	29,41%	23,23%	15,22%	42,12%	34,36%	35,08%	34,36%
	maxTotalEntropy	33,65%	25,33%	12,87%	42,12%	31,44%	32,80%	31,73%
	maxWrong	30,06%	17,96%	11,95%	42,12%	38,59%	40,40%	38,59%
	random	30,05%	22,64%	15,02%	42,12%	34,42%	37,67%	33,76%
Average - L/TOTAL	**maxEntropy**	18,63%	43,25%	60,44%		34,44%	30,61%	34,44%
	maxInfoGain	18,81%	33,86%	53,85%		32,56%	29,13%	32,88%
	maxStrangeness	29,01%	44,36%	61,67%		24,69%	20,03%	24,69%
	maxTotalEntropy	17,81%	37,92%	**67,76%**		31,49%	27,47%	30,60%
	maxWrong	25,58%	52,46%	66,41%		8,86%	5,02%	8,84%
	random	21,74%	44,70%	65,89%		23,41%	13,63%	24,60%
Average - OK+L/TOTAL	**maxEntropy**	54,60%	68,10%	77,78%	42,12%	65,52%	62,20%	65,52%
	maxInfoGain	51,22%	60,10%	71,93%	42,12%	64,33%	61,40%	64,33%
	maxStrangeness	58,43%	67,58%	76,89%	42,12%	59,04%	55,12%	59,04%
	maxTotalEntropy	51,46%	63,25%	**80,63%**	42,12%	62,92%	60,26%	62,34%
	maxWrong	55,64%	70,41%	78,36%	42,12%	47,44%	45,42%	47,43%
	random	51,79%	67,34%	80,91%	42,12%	57,83%	51,30%	58,36%
Average - IN1+L/TOTAL	**maxEntropy**	88,66%	93,19%	95,10%	85,45%	94,42%	93,18%	94,42%
	maxInfoGain	89,75%	91,83%	93,83%	85,45%	93,70%	92,76%	93,70%
	maxStrangeness	88,32%	90,84%	92,84%	85,45%	92,59%	90,26%	92,59%
	maxTotalEntropy	87,78%	91,70%	**95,32%**	85,45%	93,54%	92,30%	92,95%
	maxWrong	90,60%	93,76%	95,14%	85,45%	88,56%	86,96%	88,56%
	random	88,05%	91,27%	93,91%	85,45%	92,54%	89,55%	92,29%

the teacher will do more work, and therefore feed more information into the BN. As a matter of fact, the role of choice and termination strategies is just to find out the best way to save teachers' work while preserving a reliable inference.

Last but not least, by comparing gain in accuracy (OK+L)/TOTAL and lengthier grading L/TOTAL, we can see a kind of "effort leak" on teacher's side: the increase in accuracy is somehow not proportional to the additional work (lower, infact). In other words, a greater teacher's effort does not correspond to an equally higher accuracy of inferred grades. For this reason, more investigation is required regarding the CPT tables used for both C|K and J|K, and the starting P(K), since these elements can significantly affect information propagation and therefore the final outcome.

7 CONCLUSIONS

This paper has presented an analysis of factors affecting automatic assessment based on teacher-mediated peer evaluation. We presented results from experiments involving the OpenAnswer system, designed to support peer evaluation of open ended questions. The goal of the devised approach is to improve efficacy and efficiency of semi-automatic grading of open answer tests, as well as to teach the students evaluation skills.

Table 5: The results are obtained by adding teacher's grade with P(K)=TgrDist (we assume to know the class knowledge state as a distribution, not as individual values) and for probability to value (label P2VAL) = wSum, using CPT2; teacher grading is carried out using different strategies to choose the next answer to grade, and different termination conditions.

TgrDist	wSum	TERMINATION						
Data	**STRATEGY**	**noFlip1**	**noFlip2**	**noFlip3**	**none**	**noWrong**	**noWrong2**	**noWrong3**
Average - OK/TOTAL	**maxEntropy**	38,76%	31,01%	21,53%	45,60%	34,41%	35,97%	34,41%
	maxInfoGain	39,03%	30,87%	23,68%	45,60%	35,53%	37,02%	35,53%
	maxStrangeness	38,63%	28,11%	21,84%	45,60%	37,91%	40,01%	37,91%
	maxTotalEntropy	40,11%	33,95%	21,28%	45,60%	34,55%	36,77%	34,55%
	maxWrong	38,06%	27,55%	20,99%	45,60%	41,77%	43,61%	42,25%
	random	35,99%	27,16%	18,31%	45,60%	38,74%	41,23%	38,74%
Average - L/TOTAL	**maxEntropy**	16,72%	33,24%	53,99%		33,21%	25,81%	33,21%
	maxInfoGain	15,86%	35,74%	51,83%		30,42%	22,93%	30,21%
	maxStrangeness	16,59%	38,99%	54,60%		22,46%	16,42%	22,46%
	maxTotalEntropy	15,94%	31,68%	54,37%		30,54%	24,09%	30,54%
	maxWrong	16,61%	39,08%	53,51%		10,55%	3,85%	8,71%
	random	16,78%	41,27%	59,94%		23,88%	13,57%	23,88%
Average - OK+L/TOTAL	**maxEntropy**	55,48%	64,25%	75,51%	45,60%	67,63%	61,78%	67,63%
	maxInfoGain	54,89%	66,61%	75,51%	45,60%	65,95%	59,95%	65,74%
	maxStrangeness	55,22%	67,10%	76,44%	45,60%	60,37%	56,43%	60,37%
	maxTotalEntropy	56,05%	65,63%	75,65%	45,60%	65,08%	60,86%	65,08%
	maxWrong	54,67%	66,63%	74,50%	45,60%	52,32%	47,46%	50,97%
	random	52,76%	68,43%	78,26%	45,60%	62,62%	54,80%	62,62%
Average - IN1+L/TOTAL	**maxEntropy**	90,92%	93,29%	95,42%	87,05%	94,68%	93,19%	94,68%
	maxInfoGain	89,82%	93,09%	95,10%	87,05%	94,35%	93,39%	94,35%
	maxStrangeness	88,19%	90,32%	92,55%	87,05%	91,38%	90,16%	91,38%
	maxTotalEntropy	91,43%	93,17%	**95,98%**	87,05%	93,61%	92,70%	93,61%
	maxWrong	90,07%	93,84%	95,61%	87,05%	90,44%	88,02%	89,26%
	random	88,23%	92,97%	95,80%	87,05%	92,32%	90,07%	92,32%

The educational practice of open ended questionnaires represents a very effective assessment tool but requires much grading effort by the teacher. On the other hand the practice of peer assessment would train the meta-cognitive abilities of students. So, the goals mentioned above also aim to provide the teacher with an effective environment, where a wider usage of open answer questionnaires is encouraged and supported, while the teacher is relieved of a significant part of the consequent grading work, so to concentrate on higher level tasks, such as the definition of questions and of the criteria to assess them.

It appears that it is still necessary to gain a deeper understanding of the effect of different set-up choices and modelling parameters on the final results. The reason why this kind of investigation is crucial for the final outcomes, is because the elements conditioning the system behaviour do not represent pure operation parameters, but should reflect a real understanding of pedagogical and educational issues. The fact to reflect on is that some "manual" adjustments of probability distributions, obtained through a field experience in educational tasks, achieve better result than "reasonable" mathematical considerations. Moreover, even in the best starting set-up, the work of the teacher still appears to be of crucial importance for the overall system reliability. This is due to a kind of implicit knowledge that is entailed in the educational process, a thing that is difficult to formalize through automatic operational rules.

About future work, on the side of experimental settings we are pursuing application of the framework to the case of formal algebra (Formisano et al. 2000, 2001), on the spur of work done in (El-Kechaï et al. 2011). Another application of the OpenAnswer approach to peer-evaluation will be in regard to the support for teachers of the retrieval and selection of learning objects in courses contruction, in the line of work done in (Limongelli et al. 2012, 2013, 2015, 2016; Gentili et al. 2001; Sciarrone 2013). Regarding the development of the framework, we will investigate in particular the role of propagation of information between a sequence of assessment sessions. We are encouraged in doing this by the good results obtained when using a distribution of values for the expected initial student knowledge that is given by considering the overall class state. In the present work, we carried out a kind of systematic investigation on the dependence of the correctness of a learner's answer, from her state of knowledge (C|K). Another point to investigate in the future will be the best distribution to use for J|K, i.e., the ability to judge given e certain state of knowledge. Actually, this reasonably appears to be a further crucial parameter in modelling the inference process.

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