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Nader Nashed, Christine Lahoud, Marie-Hélène Abel

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Contextual and sentimental teachers' peer recommendations

Nader N. Nashed
HEUDIASYC

Université de Technologie de Compiègne
Compiègne, France
nader.nashed@utc.fr
Université Française d'Égypte
Cairo, Egypt
nader.nashat@ufe.edu.eg

Christine Lahoud
Université Française d'Égypte
Cairo, Egypt
christine.lahoud@ufe.edu.eg

Marie-Hélène Abel
HEUDIASYC
Université de Technologie de Compiègne
Compiègne, France
marie-helene.abel@utc.fr

Abstract—The current recommender systems' approaches favor item's recommendation over peer's recommendation. Such virtual information systems do not allow face-to-face communication for collaborative knowledge exchange between peers. However, the on-going worldwide situation affects the sentimental state and especially for a teacher who struggle to adapt his course's contents according to current variables. These challenges can be mitigated through personalized peer recommendations for teachers. A more-experienced teacher can provide the required support for a less-experienced one in the form of knowledge sharing. This paper proposes a matching approach to provide peer recommendations for teachers in consonance with their context and sentimental state. The peer recommendation aids the teacher to collaborate with other teachers in the form of experience sharing and knowledge sharing. Furthermore, the paper highlights the similarity measurement criteria for contextual and sentimental matching algorithm in addition to predefined rules. At the end, the paper discusses the effectiveness of the algorithm application with a real-life scenario.

Keywords—sentiment, recommendation, recommender systems, semantic web, educational resource, education, teacher, CARS

I. INTRODUCTION

During the past two years, the number of new emerging virtual teaching and learning environments has increased significantly. As a result, these virtual environments had a great impact on the educational sector [1]. Accordingly, teachers must change their teaching methodologies and the young inexperienced teachers are no exception. These young teachers do not have the appropriate expertise level to deal with all these rapid changes. Most probably, the sentimental state of these teachers is an accurate indication for the difficulties that can be faced by the teacher. Collaboration between teacher from different levels of expertise has a recognizable impact on the work environment as well as the sentimental state of the teachers [2]. This collaborative work provides technical support as well as the emotional support for all participating teachers.

Recommender Systems (RSs) is defined as information filtering systems that offers personalized recommendations

according to a user's context [3]. In our context, the recommendations can be in the form of pedagogical resources as well as peer teachers. These RSs are implemented to facilitate the knowledge sharing as well as helping people help each other [4]. Unfortunately, these advantages cannot be achieved efficiently without considering the context of the offered help in addition to the person's context. Context-Aware Recommender Systems (CARS) are more effective than other RSs approaches in considering the multiple factors of a person's context in order to offer the suitable help. However, in our case, it is a more challenging mission to take into consideration the teacher's multiple contexts in addition to the sentimental state.

In this research, a new peer-recommendation approach is introduced trying to solve the multiple challenges of this problem: sentimental state, surrounding environments, and the teacher's profile. The new methodology offered by this paper, selects the appropriate context factors for a teacher and enforces the sentimental state matching. Therefore, this research offers sentimental support as well as technical support in the form of a peer to offer collaboration for a certain pedagogical resource or topic. The paper is organized as follows: Section II introduces the state of art of related work to contextual and sentimental state consideration in CARS and peer recommendations approaches. Section III introduces the multiple steps of the proposed methodology. Section IV provides an illustration supported with examples on the benefits of the proposed approach. In Section V, this paper is concluded, and future perspectives are stated.

II. RELATED WORK

The related research to our work is divided into two categories: peer recommendation in RSs and context factors selection approaches in CARS. Hence, Subsection II-A discusses the latest trends of peer recommendation, especially in the educational context. On the other hand, Subsection II-B reviews the previous contextual factors extraction.

A. Peer Recommendations

The initial understanding of the term “peer recommendations”, is directed towards the peer-to-peer recommendation which is not the purpose of this research. In this paper’s context, peer recommendation is defined as introducing a peer (person) as the recommended item to a user (person). This definition is not adapted by any of the reviewed approaches, but many approaches benefit from the power of the peer-based recommendations. The term “peer learning” is defined as the process of collaboration between two or more equals or matched companions to acquire knowledge and skills in a certain context in which they provide the required support and help to each other [5], [6]. From the previous definition, it can be deduced that most of the research input in this aspect, is directed towards the different types of learners. Therefore, this subsection discusses the latest research in this aspect and connects them to our research.

The concept of Recommendation in Personalised Peer Learning Environments (RiPPLE) was introduced by Khosravi [7] to describe the information systems, including recommender systems, that provide the required personalized learning support for the targeted users. In another work related to the previous concept, Khosravi et al [8] introduced a new question sharing approach based on a collaborative filtering algorithm. In this approach, learners express their knowledge gaps by posting questions through a forum. Potts et al. [9] introduced a course-level peer recommender system to provide peer-to-peer collaboration between learners to fill the knowledge gaps of these learners. The algorithm recommends questions for learners to explore, review or answer, based on their skills. Labarthe et al. [10] conducted an experiment on a project management course that was held over a MOOC system. Their recommender provided peer recommendations within a group of learners of the same interest and based on the learners’ overall performance. During later research related to the previous experiment [11], learners were asked if they want to chat with other peers of the same interest. The research proved through this experiment that the learners tend to use this peer recommendation to express their emotion rather than the learning support.

The systematic review conducted by Deschenes [12], concludes that there is a need to invest more research effort towards peer recommender systems in the learning context. Moreover, we could not find any teacher peer recommender systems in the educational context. Therefore, this paper introduces a new research input towards a topic that lacks attention, and it introduces a needed help for teachers.

B. Context Representation and Contextual Factors Extraction

During the latest research approaches, there is a noticeable increase in the ontology-based context description, especially in the e-learning information systems [13]. Teacher Context Ontology (TCO) is one of the latest ontologies that offers

an extensive description of the teacher’s context [14]. The ontology represents the different contexts that a teacher coexists: living context, working context, and teaching resources’ orientation in the different contexts. Mood Detection Ontology (MDO) extends TCO by including sentimental state of the teacher while interacting with the teaching resources [15]. An ontology provides a step forward towards a better context representation for input data, recommendation rules, output recommendation, and recommendation evaluation [16].

The process of extracting the contextual factors is divided into two steps: context factors selection, and context factors weighting [17]. The factors selection is considered a major challenge in any CARS, as a factor’s relevance to the context is a difficult interrogation [18]. Therefore, Zheng [19] introduces an enhancement for the context-aware recommendation algorithm by proposing the factorizing of context into scalable factors. Furthermore, Zheng [20] also extended this enhanced algorithm by introducing a context-aware recommender approach for multiple contexts problem. Li et al. [21] provided a statistical solution for the multi-dimensional problem in the context-aware recommendation approaches by using random forest algorithm to select and weight the contextual factors. The contextual factors weighting can be achieved by several optimization algorithms such as Particle Swarm Optimisation (PSO) or the gradient descent optimization [22] with an error correction using a fitness function such as Mean Square Error (MSE) or Root Mean Square Error (RMSE) [22], [23]. But some of the reviewed approaches opted out the factors’ selection process and only weighs all available factors which results in less personalized recommendations [24], [25].

For all the reviewed articles, we can notice the lack of sentimental state consideration as one of the contextual factors, and the lack of sufficient research output towards the selection and weighting of educational contextual factors and more precisely, in the teacher context.

III. METHODOLOGY

The context/situation matching between peers, is a complicated process that can be changeable according to different persons. The person’s context is described by a set of factors/conditions. These factors are dependent on the person’s situation which prevents the unification of the selected factors. Moreover, predictions of context-aware recommender systems, can be imprecise if all contextual factors were weighted equally. The personalized process of weighting and selection of contextual factors improves the recommendations’ quality according to each teacher. Therefore, the proposed approach introduces an algorithm to weigh and select the contextual factors, in addition to a sorted list of peer recommendation according to the teacher’s contextual representation by the teacher-context ontology (TCO) [14] and the mood detection ontology (MDO) [15]. First, a teacher T is asked if she/he

Algorithm 1 An overview of the proposed algorithm

Input: C_{resr}^T : current context of a teacher T and concerning the current resource $resr$
 H^T : history of current teacher T
Output: sortedList : sorted list of all matching teachers
begin
1: **if** (getMood(T) == 'negativeMood' && offerHelp == true)
 then
2: $W_{global} = \text{contextExtractionAlgo}(C_{resr}^T, H^T)$;
3: matchingList = contextMatching(W_{global});
4: sortedList = sortList(matchingList);
5: **end if**
6: **return** sortedList;
end

needs help when a negative mood is detected during her/his interaction with a resource $resr$. A negative mood can be defined as the sentimental commitment level below the personal average neutral commitment level and it is detected by the MoodFlow@doubleYou technology [15]. If the teacher accepts that help is needed or she/he is not sure, the algorithm starts to find a peer recommendation for this teacher. The algorithm is divided into three steps: selection/weighting of factors for T with respect to $resr$ which returns a list of context factors f associated with a weight w , generation of matching peer list by computing the similarity between the teacher T and the other peer teachers, and at the end, sorting the matching list according to the pre-defined semantic web rules using scoring and ranking for the peer candidates, as shown in Algorithm 1.

A. Selection and weighting contextual factors

This approach selects the contextual factors and weighs it in correspondence to a specific teacher T who interacts with a specific resource $resr$ which introduces precise description of this teacher's context C_{resr}^T and high personalization level of peer recommendations. Algorithm 2 starts with the *factorsExtraction* algorithm that selects the factors and computes the initial weights W_{init} of each factor $f_i \in F$. The initial weights are optimized by one of the optimization-based algorithms such as gradient descent approaches and particle swarm optimization (PSO) [24], [25]. The root mean squared error (RMSE) is used as the fitness function for the optimization algorithm for error minimization.

The *factorsExtraction* function, as shown in Algorithm 3, selects a set of contextual factors n' from all context factors n under the condition $n' < n$ for a teacher's context C_{resr}^T . A weight w_i is calculated for each contextual factors f_i with respect to all teachers T_s that interacts with a resource $resr$. The algorithm excludes teachers and factors from the final list according to a given similarity threshold and a weight threshold, respectively. The similarity threshold thr_1 is used to select teachers with similarity score greater than a precalculated similarity score for a teacher T , while the weight threshold thr_2 is responsible for the factors' selection

Algorithm 2 Contextual factors extraction algorithm

Input: C_{resr}^T : current context of a teacher T and concerning the current resource $resr$
 H^T : history of current teacher T
 FF : fitness function
Output: $W_{global} = \{ \langle f_1, w_1 \rangle, \dots, \langle f_{n'}, w_{n'} \rangle \}$: set of final weights w_i for each of the selected n' context factor f_i from the n initial context factors where $n' < n$.
begin
1: $W_{init} = \text{factorsExtraction}(C_{resr}^T, H^T)$;
2: $W_{global} = \text{weightsOptimization}(W_{init}, FF)$;
3: **return** W_{global}
end

with a calculated initial weight greater than the average of all contextual factors' weights. The similarity function between two teachers *calculateSimilarity* computes the semantic similarity to ensure an effective representation of the actual context of both teachers. It is computed by calculating the teachers' distance similarity scores from TCO contextual instance corresponding to each teacher. This semantic similarity approach is also used to get the context matching list of peer teachers *matchingList* in Algorithm 1.

In order to enforce the sentimental state of the peer recommendation, a coefficient $coef_{+ve}$ is multiplied by the calculated similarity for a similar teacher T_s to prioritize the contextual mood factor [26]. The usage of such coefficient is reflected on the computed initial weight w_i corresponding to the mood factor f_i . On the other hand, if there is few or no results for teachers with a positive mood (the sentimental commitment level above a person's average neutral commitment level), the algorithm adapts normally with the new situation, selecting the factors and assigning their initial weights.

The initial weight of each factor is determined by averaging the mean semantic similarity scores of all selected teachers Sim^{resr} and the variance of these teacher's rating for the current resource $resr$ according to Equations 1,2, where r_i^{resr} is the rating for selected teacher i for the resource $resr$, \bar{r}^{resr} is the average rating for this resource, and nb_T is the number of selected teachers.

$$Sim_{var}^{resr} = \frac{\sum (r_i^{resr} - \bar{r}^{resr})^2}{nb_T} \quad (1)$$

$$w_{kinit} = \frac{Sim^{resr} + Sim_{var}^{resr}}{2} \quad (2)$$

B. Sorting using semantic web rules

The Semantic Web Rule Language (SWRL) ¹ is a rule markup language that is used with Ontology Web Language

¹<https://www.w3.org/Submission/SWRL/>

Algorithm 3 Variance-based similar-teachers contextual factors selection algorithm

Input: $C_{resr}^T = (T, F, rating, resr)$: current context of a teacher T and concerning the current resource $resr$ with rating r , represented by context factors F .
 H^T : history of current teacher T .
 thr_1 : given similarity threshold.
 thr_2 : given weight threshold.
 $coef_{+ve}$: positive mood contextual factor enforcing coefficient.

Output: $W_{init} = \{ \langle f_1, w_{1_{init}} \rangle, \dots, \langle f_{n'}, w_{n'_{init}} \rangle \}$: set of initial weights $w_{i_{init}}$ for each of the n' context factor f_i .

```

begin
1: for all  $f_k \in F$  do
2:    $nb_T = 0$ ;
3:    $Sim_{total} = 0$ ;
4:   for all  $\langle resr_j, c_j^{T_s} \rangle \in H^T$  do
5:     if  $(resr_j == resr)$  then
6:        $similar(T_s, T) = \text{calculateSimilarity}(C_{resr}^T, C_{T_s}^T)$ ;
7:       if  $(similar(T_s, T) \geq thr_1)$  then
8:          $nb_T ++$ ;
9:          $rating_{T_s} = \text{getRating}(T_s, resr)$ ;
10:         $similarTeachersList.add(rating_{T_s})$ ;
11:        if  $(f_k == 'mood' \&\& (\text{getMood}(T_s) == 'positiveMood' || \text{getMood}(T_s) == 'neutralMood'))$  then
12:           $similar(T_s, T) *= coef_{+ve}$ ;
13:        end if
14:         $Sim_{total} += similar(T_s, T)$ ;
15:      end if
16:    end if
17:  end for
18:   $sim^{resr} = \frac{Sim_{total}}{nb_T}$ ;
19:   $sim_{var}^{resr} = \text{getVariance}(similarTeachersList)$ ;
20:   $w_{k_{init}} = \text{average}(sim^{resr}, sim_{var}^{resr})$ ;
21:  if  $(w_{k_{init}} \geq thr_2)$  then
22:     $W_{init} = \text{addFactor}(\langle f_k, w_{k_{init}} \rangle)$ ;
23:  end if
24: end for
25: return  $W_{init}$ ;
end

```

(OWL)² to express logical rules into readable syntax. In this approach, SWRL rules are used to sort the teachers' peer list generated from *contextMatching* function. For each teacher T_i in the generated list *matchingList*, the rules are applied to reason the A-box instance of this teacher. A total score is calculated by counting the number of the satisfied rules except for rule 5 with double counts, as it is responsible for the sentimental state detection. Then, the list is sorted according to a descending order of the obtained scores. At the end, the teacher is asked for the preferred level of expertise for the recommended peer.

Some of the rules in Table I are used for teacher classification only. For example, rules 1,2, and 3 identify the experience level of the teacher according to TCO classification: Novice, Intermediate, and Expert. Rule 4 detects if the compared teacher's years of experience is more than the current one to determine the knowledge and beneficial level for this match. Rule 5 checks if the recommended teacher has a better sentimental state (mood) than the current teacher. This rule enforces the positive influence of the sentimental state of one person on another

person or an organization [27]. Rule 6 matches the teaching styles of both teachers as it is said the difference in styles has its impact on the collaboration between two peer teachers [28], [29]. Rule 7 checks the spoken languages by the two teachers which facilitates the collaboration and enhances the communication between them.

The living and working environments have a great impact on a teacher's personality as well as the working methodologies [30]. Therefore, rule 8 checks if there is a matching between the type of the two teachers' living environment, such as rural, urban, sub-urban, etc., while rule 9 matches the country where each teacher lives in. Rules 10, 11 compare the working environment in terms of the environment type and the educational institution level. The final rule, rule 12, checks if the two teachers belong to the same field of science. These rules work as an enforcer for the list order but are not used to exclude any of the recommended teachers.

IV. DISCUSSION AND SCENARIOS

After generating the list of teachers' peer recommendations, our main goal is to enforce various measures using semantic rules during the peer matching process to illustrate the impact of applying such rules on a teacher context. The sentimental state of teacher, expertise level, work and living environments, and field of science are the selected concepts in our approach, in addition to language and teaching style. The usage of SWRL rules to leverage these essential concepts proved to be effective. Example 1 illustrates the importance of the SWRL rules in enforcing the desired concepts.

Example 1: Let's assume that teacher T_A is a novice teacher with a negative mood while viewing a pedagogical resource and the teacher agrees to the offered help, as shown in Figure 1. Algorithm 2 computes the list of contextual factors as well as their final weights W_{global} for this teacher's context. The semantic similarity calculated within *contextMatching*, indicates that the peer recommendation T_C obtains higher similarity score $Sim(A, C)$ than T_B despite the negative mood of this teacher while viewing the same resource. However, when the SWRL rules are applied to both recommendations, teacher T_B obtains higher score $Score_{SWRL}(A, B)$ than T_C by enforcing the positive sentimental state of teacher T_B as well as the teaching style. The *sortList* function offers the final list to the teacher in the following order: teacher T_B , teacher T_C .

$$W_{global} = \{ \langle \text{Language}, 0.2 \rangle, \langle \text{Science}, 0.4 \rangle, \langle \text{Mood}, 0.3 \rangle, \langle \text{Working Environment}, 0.35 \rangle, \langle \text{Living Environment}, 0.1 \rangle \}$$

$$T_A = \{ \{ \text{Language 1, Language 2} \}, \text{Science 1, Negative, Small City, Small City} \}$$

$$T_B = \{ \{ \text{Language 1, Language 2, Language 3} \}, \text{Science 1, Positive, Large City, Small City} \}$$

$$T_C = \{ \{ \text{Language 2, Language 3} \}, \text{Science 1, Negative, Small City, Small City} \}$$

²<https://www.w3.org/OWL/>

TABLE I
SWRL RULES FOR PEER'S LIST SORTING

#	Rule
1	tco:teacher(?t)^tco:hasYearsOfExperience(?t,?ex)^sqrbl: lessthan(?ex,5)-)tco:noviceTeacher(?nt)^rdf:is-a(?t,?nt)
2	tco:teacher(?t)^tco:hasYearsOfExperience(?t,?ex) ^sqrbl:lessthan(?ex,10)^sqrbl:greaterthan(?ex,5)-)tco: intermediateTeacher(?it)^rdf:is-a(?t,?it)
3	tco:teacher(?t)^tco:hasYearsOfExperience(?t,?ex)^sqrbl: greaterthan(?ex,10)-)tco:expertTeacher(?xt)^rdf:is-a(?t,?xt)
4	tco:teacher(?t)^tco:hasYearsOfExperience(?t,?ex)^tco: teacher(?ts)^tco:hasYearsOfExperience(?ts,?exs)^sqrbl: greaterthan(?exs,?ex)-)sqrwl:select(?ts)
5	mcc:InteractionActivity(?e)^mcc:hasActor(?e,?acc)^mdo: resultsIn(?e,?m)^mdo:mood(?m)^mdo:hasValue(?m,?v)^mcc: hasActor(?e,?accs)^mdo:resultsIn(?e,?ms)^mdo:mood(?ms) ^mdo:hasValue(?ms,?vs)^sqrbl:greaterthan(?vs,?v)-)sqrwl: select(?ts)
6	tco:teacher(?t)^tco:hasTeachingStyle(?t,?tch) ^tco:teacher(?ts)^tco:hasTeachingStyle(?ts,?tchs) ^sqrbl:stringEqualIgnoreCase(?tch,?tchs)^sqrbl: stringEqualIgnoreCase(?tch,"MixedStyle")-)^sqrwl:select(?ts)
7	tco:teacher(?t)^tco:hasLanguage(?t,?lan)^tco:teacher(?ts)^tco: hasLanguage(?ts,?lans)^sqrbl:contains(?lan,lans)-)^sqrwl: select(?ts)
8	tco:teacher(?t)^tco:livesIn(?t,?livenv)^tco: LivingEnvironment(?livenv)^tco:is-a(?livenv,?env) ^tco:environment(?env)^tco:hasType(?env,?envtype) ^tco:teacher(?ts)^tco:livesIn(?ts,?livenvs)^tco: LivingEnvironment(?livenvs)^tco:is-a(?livenvs,?envs)^tco: environment(?envs)^tco:hasType(?envs,?envtypes)^sqrbl: equal(?envtype,?envtypes)-)^sqrwl:select(?ts)
9	tco:teacher(?t)^tco:livesIn(?t,?livenv)^tco: LivingEnvironment(?livenv)^tco:is-a(?livenv,?env)^tco: environment(?env)^tco:hasCountry(?env,?coun)^owl: country(?coun)^tco:teacher(?ts)^tco:livesIn(?ts,?livenvs)^tco: LivingEnvironment(?livenvs)^tco:is-a(?livenvs,?envs)^tco: environment(?envs)^tco:hasCountry(?envs,?couns)^owl: country(?couns)^sqrbl:equal(?coun,?couns)-)^sqrwl:select(?ts)
10	tco:teacher(?t)^tco:worksIn(?t,?inst)^tco: EducationalInstitution(?inst)^tco:evolvesIn(?inst, ?workenv)^tco:WorkingEnvironment(?workenv)^tco: is-a(?workenv,?env)^tco:environment(?env)^tco:hasType(?env, ?envtype)^tco:teacher(?ts)^tco:worksIn(?ts,?insts)^tco: EducationalInstitution(?insts)^tco:evolvesIn(?insts,?workenvs) ^tco:WorkingEnvironment(?workenvs)^tco:is-a(?workenvs, ?envs)^tco:environment(?envs)^tco:hasType(?envs,?envtypes) ^sqrbl:equal(?envtype,?envtypes)-)^sqrwl:select(?ts)
11	tco:teacher(?t)^tco:worksIn(?t,?inst)^tco: EducationalInstitution(?inst)^tco:hasEducationLevel(?inst, ?edulvl)^dterms:EducationLevel(?edulvl)^tco:teacher(?ts) ^tco:worksIn(?ts,?insts)^tco:EducationalInstitution(?insts) ^tco:hasEducationLevel(?insts,?edulvls)^dterms: EducationLevel(?edulvls)^sqrbl:equal(?edulvl,?edulvls)-) sqrwl:select(?ts)
12	tco:teacher(?t)^tco:hasScience(?t,?sci)^modsci:Science(?sci) ^tco:teacher(?ts)^tco:hasScience(?ts,?scis)^modsci: Science(?scis)^sqrbl:equal(?sci,?scis)-)^sqrwl:select(?ts)

$$Sim(A, B) = \frac{1*0.2+1*0.4+1*0.3+0*0.35+1*0.1}{0.2+0.4+0.5+0.35+0.1} = 0.74$$

$$Sim(A, C) = \frac{1*0.2+1*0.4+0*0.3+1*0.35+1*0.1}{0.2+0.4+0.5+0.35+0.1} = 0.78$$

$$Score_{SWRL}(A, B) = 8/10 = 0.8$$

$$Score_{SWRL}(A, C) = 6.5/10 = 0.65$$

The illustrated case can result in a different output if the contextual factors were selected without the mood enforcing approach. As previously stated, the sentimental analysis of the user has a remarkable impact on the provided results. This paper enforces the sentimental state of the teacher by enforcing the contextual factor f_{mood} in Algorithm 3 and by applying the SWRL rules in Table I. If one of these two steps is escaped,

the final recommendations are not of the desired quality. In Example 1, the mood contextual factor fails to prioritize the positive-mood teacher recommendation, but the SWRL rules readjusted the final recommendations list. Therefore, it can be said that this approach is more efficient regarding the sentimental state point-of-view.

Accordingly, the mentioned rules can be reordered or modified to obtain different results. For example, if Rule 12 is replaced with a different rule that matches the precise science field of both compared teachers, the list's order will be affected and accordingly the impact of the result on the teacher's sentimental state. Moreover, the rules can be increased to adjust the resulting list towards another approach, resulting in a flexible algorithm that can adapt to the different teachers' situations. TCO ontology and the SWRL rules provide a human understandable situation that can be easily evaluated using readable context as in Figure 1 and logical rules as in Table I. The reviewed approaches target only a user in a unique situation without any generalization or problem abstraction. At the end, the provided results in these circumstances, cannot be evaluated except by the teacher. Hence, the teacher's evaluation of result list is used to recommend the same peer for other teachers with the same context which enhances the computing overhead for large datasets used by other approaches.

V. CONCLUSION AND PERSPECTIVES

At the end, we can conclude that this paper introduced a new selection and weighting of contextual factors for the teacher's peer recommendations using the ontology representation of TCO and MDO. This approach includes a new sorting algorithm that uses semantic rules to enforce certain factors. The sentimental state of the recommended teacher is one of the enforced factors that is believed to affect the current teacher state. The peer recommendations form a new opportunity to encourage the teachers' collaboration through the current undeniable rapid changes in the living and working environments. The proposed algorithm provides a methodology for selecting and weighting the contextual factors, extracting the ones that accurately describes a certain teacher's context. The coupling of selection and weighting algorithms is not followed by all the reviewed approaches which proves its efficiency. Furthermore, this approach raises promising flexibility that allows applying it to other contexts rather than the teacher's context. If a different contextual ontology with a new set of rules replaces the current one, the algorithm shows a high degree of flexibility when theoretically tested on other contexts.

This work can be enhanced through multiple approaches to explore. The computed factors and its weights can be stored into a dataset that is later used to learn the behavior of teachers and then, match the similar contexts with the previous obtained results. This proposition will reduce the computational overhead of finding new set of factors and weighting it with each recommendation process. Neural networks and deep learning approaches are other approaches that can be

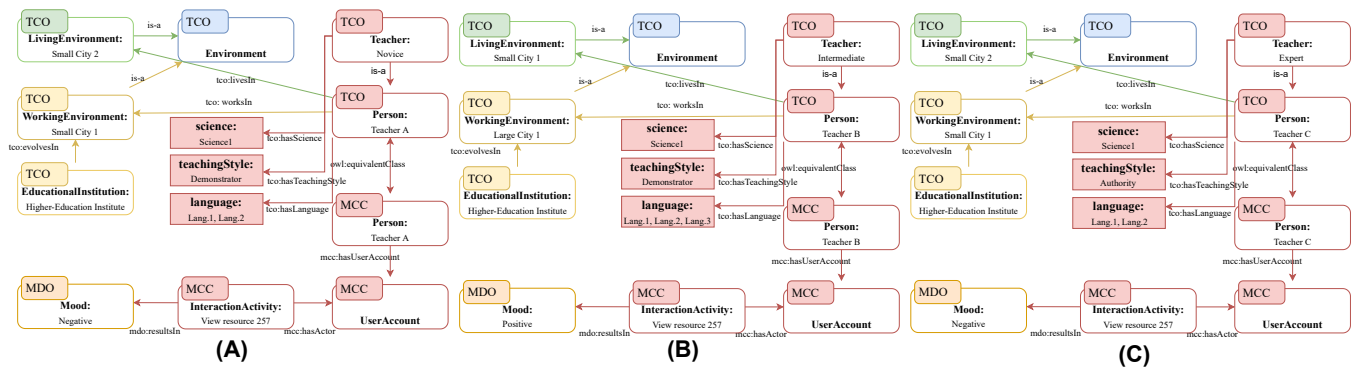


Fig. 1. A-Box instances of TCO for Exmaple 1.

of good impact on the weights optimization calculation and can provide better learning algorithm. Overall, the proposed approach opens more possibilities for further investigations and enhancements to explore.

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- of good impact on the weights optimization calculation and can provide better learning algorithm. Overall, the proposed approach opens more possibilities for further investigations and enhancements to explore.
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