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**Abstract.** Nowadays, more and more collaborative tools are available to support users' remote collaborations. Its increasing amount makes users struggle in managing and retrieving information about their collaborators during collaboration. To solve this problem, many decision support systems have been developed quickly, such as recommender systems and context-aware recommender systems. However, the performances of different algorithms in such systems are relatively unexplored. Based on our three proposed context-aware collaborator recommendation algorithms (i.e., PreF1, PoF1, and PoF2), we are interested in analyzing and evaluating their performances in terms of accuracy and time efficiency. The three algorithms all process the context of collaboration by means of ontology-based semantic similarity, but employ the similarity following two approaches respectively, to generate context-aware collaborator recommendations. In this paper, we present how to test, analyze, and evaluate the performances of the three context-aware collaborator algorithms in terms of accuracy and time efficiency.

**Keywords:** Context-aware recommendations · Collaborator · Collaboration context · Ontology-based semantic similarity.

## 1 Introduction

With the development of information technology, increasingly more collaborative tools have been provided for users' remote collaborations. This makes it difficult for users to organize and manage the heterogeneous information among these tools within collaborations. Particularly, users find it difficult to retrieve information about collaborators and therefore cannot work with appropriate collaborators to advance their collaborations. To help users make decisions about collaborators, recommender systems (RS) are designed and applied [18], which can generate collaborator recommendations for them. However, such recommendations are sometimes not quite relevant, due to the missing consideration of

context [3]. For instance, while generating collaborator recommendations, information of user's collaboration place and time should also be considered, which can influence users' needs for their collaborators. To incorporate context into recommendation generation processes, a new type of RS has been proposed: Context-Aware Recommender System (CARS). Despite the quick development of CARS, there is little studies on analyzing and evaluating the performance of different context-aware recommendation algorithms.

Therefore, we are interested in testing, analyzing, and evaluating the performance of our three proposed context-aware collaborator recommendation algorithms (i.e., PreF1, PoF1, and PoF2) [13] in terms of accuracy and time efficiency. The three algorithms all consider and compare the context of collaboration by means of ontology-based semantic similarity to generate context-aware collaborator recommendations for users. Their differences lie in where and how the semantic similarities are applied in recommendation generation processes. Specifically, PreF1 employs semantic similarities in the pre-processing step, following contextual pre-filtering approach [3]. As for PoF1 and PoF2, they utilize semantic similarities in post-processing step, based on contextual post-filtering approach [3]. Besides, all the three algorithms can be realized and tested in a public dataset of scientific collaborations. This allows us to evaluate their performances through three metrics: F1, mean absolute error, and execution time. These results then make it possible to analyze both advantages and disadvantages of the three algorithms in producing context-aware collaborator recommendations.

The remainder of this paper is constructed as follows. Section 2 studies context-free and context-aware recommender systems. Section 3 presents our contributions in (i) developing three context-aware collaborator recommendation algorithms (i.e., PreF1, PoF1, and PoF2) based on a collaboration context ontology and an ontology-based semantic similarity, (ii) applying a dataset to test them, (iii) analyzing and comparing their performances in terms of accuracy and time efficiency through three metrics. We then discuss the strengths and weaknesses of the three context-aware collaborator recommendation algorithms in Section 4. Finally, some conclusions and future work are shown in Section 5.

## 2 Related Work

This section distinguishes context-free and context-aware recommender systems (RS). Section 2.1 and 2.2 separately explore the approaches and techniques that can be used in these RSs. We then discuss their differences and relationships in Section 2.3.

### 2.1 Context-free recommender systems

Context-free RSs[3] gather and utilize two types of information to provide recommendations: **user** and **item** [21]. Here, **item** is the general term to indicate the objects that 2D RS recommends to users, while **user** indicates people who will receive these recommendations [21]. For example, in a collaborator RS, an item indicates a collaborator. Particularly, an item is characterized and sorted by its ratings that indicate how a particular user liked/preferred this item [2] [21]. Thus, the core task of 2D RSs is: Given an initial set of ratings that users explicitly or implicitly give for items, 2D RSs try to predict users' unknown ratings for items and decide which items to recommend [3] [21]. Specifically, users' ratings for items in a 2D RS can be calculated by a function as follows [2]:

$$R_{RS} : User \times Item \rightarrow Rating \tag{1}$$

where *Rating* is a totally ordered set (e.g., non-negative integers or real numbers within a certain range).

Based on the literature review, there are four main approaches to generate 2D recommendations [1] [2] [21]:

1) **Content-Based filtering (CB)** approach first creates a profile for each user and a description for each item, then predicts users' unknown ratings by comparing these user profiles and item descriptions [1] [2]. Usually, CB approaches apply and implement the following techniques: Vector Space Model (VSM), TF-IDF, Semantic Analysis (using ontology) [16], Naïve Bayes, Decision Trees [15], Neural Networks [19], Cosine similarity [15].
2) **Collaborative Filtering (CF)** approach predicts a particular user's unknown rating for an item based on the user's past behaviors, such as previous transactions and items' ratings [1]. The general assumption of CF approach is: if two users have same rating on one item, one of them is more likely to have the similar rating as the other on a different item [1] [2]. In CF approaches, the applicable techniques include Nearest neighbor [23], Pearson correlation [10], Cosine similarity [6], similarities in ontology [28], Matrix Factorization (MF), Latent Dirichlet Allocation (LDA), Singular Value Decomposition (SVD) [11].
3) **Knowledge-Based (KB)** approach utilizes specific domain knowledge about users' requirements and preferences to generate 2D recommendations [7]. Such approaches either determine unknown ratings by evaluating similarity metrics between the predefined cases and users' requirements [4], or estimate the extent to which an item can meet users' explicit requirements based on certain rules in a predefined knowledge base [7]. For KB approaches, techniques related to knowledge base and similarity measurement can be used and implemented, such as ontologies [25] and semantic similarity [22].
4) **Hybrid** approach combines two or more other previous approaches (i.e., CB, CF, and KB) to predict users' unknown ratings for items [2]. Thus,

[3] Such a RS is also mentioned as **2D RS** in the rest of this paper.

the techniques that can be used in the three previous approaches are also applicable in Hybrid approaches.

### 2.2 Context-aware recommender system

As for Context-Aware Recommender System (CARS), it is constructed by incorporating context into 2D recommendation generating process, resulting in more accurate recommendations [20]. Unlike 2D RS, CARS deals with at least three types of information: **user**, **item** and **context**. It is even possible to construct a CARS using more types of information. For example, a context-aware movie RS [1] handled information separated into 5 dimensions: user, item, place, time and companion. Thus, the rating function of a n-dimensional CARS is [1]:

$$R_{CARS} : D_1 \times D_2 \times ... \times D_n \rightarrow Rating(n \geq 3, n \in \mathbb{N}^*) \tag{2}$$

where $D_1, D_2, ..., D_n$ represent n dimensions of information (including user, item, context, ...). When $n = 3$, it becomes: $User \times Item \times Context \rightarrow Rating$.

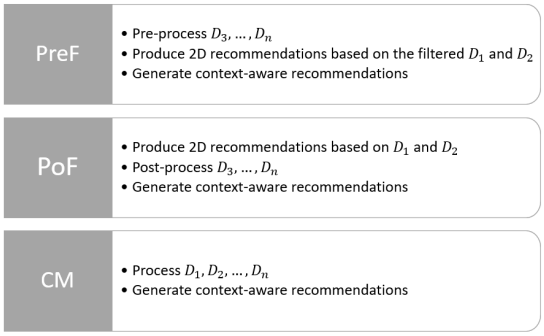


**Fig. 1.** Main steps of PreF, PoF, and CM [3].

Particularly, [3] proposed three approaches to incorporate the context in different steps of recommendation processes (see Fig. 1)[4], as follows:

- **Contextual pre-filtering (PreF)** approach first applies the context to filter ratings that are irrelevant to specific contexts [1]. It then employs $D_1, D_2$, and 2D recommendation techniques to predict unknown ratings and thus generate context-aware recommendations for users.
- **Contextual post-filtering (PoF)** approach starts with $D_1, D_2$, and 2D recommendation techniques, producing 2D recommendations. Afterwards, we utilize $D_3, ..., D_n$ to filter out the irrelevant 2D recommendation results or adjust their orders and thus generate context-aware recommendations [3].

[4] Fig. 1 also illustrates how $D_1, D_2, ..., D_n$ are utilized in different methods.

– **Contextual modeling (CM)** approach produces truly multidimensional recommendations. It deals with all dimensions of information (i.e., $D_1$, $D_2$, $D_3, ..., D_n$) in each step of the whole recommendation generation process.

### 2.3 Discussion

Based on the literature review of 2D RS and CARS, the techniques of CARS are still immature when compared to those of 2D RS. However, there is something in common between them. For example, techniques of some 2D recommendation approaches can directly serve in PreF and PoF approaches. This indicates that 2D recommendation approaches are important sources of inspiration for CARS, thus contributing to their development. Specifically, both PreF and PoF approaches can support any 2D recommendation approaches (i.e., CB, CF, KB, and Hybrid), but they require extra steps in generating context-aware recommendation: PreF needs to first filter out irrelevant ratings, as pre-processing step; PoF must filter out irrelevant 2D recommendation results, as post-processing step (see Fig. 1). Besides, CM approach necessitates more complicated rating functions to deal with all dimensions of information in the recommendation generation process (see Fig. 1). Consequently, any 2D recommendation approaches can not be directly applied in CM.

Moreover, the multidimensional information in CARS also causes difficulties: from the perspective of information volume, CM can not handle the same amount of users and items as the other two approaches (i.e., PreF and PoF). While CM needs to process information of $D_1 \times D_2 \times ... \times D_n$, the other two focus only on information of $D_1 \times D_2$. Meanwhile, as the dimensions of the information increase, the computational complexity of CM becomes higher and higher. However, for PreF and PoF, only their extra steps (pre-processing and post-processing) become more complicated. This indicates that, unlike PreF and PoF, CM is too costly when information volume and complexity are heavy. Thus, we concentrate on using PreF and PoF approaches to develop three context-aware collaborator recommendation algorithms (i.e., PreF1, PoF1, and PoF2) [13]. Particularly, PreF1 follows PreF approach, while PoF1 and PoF2 are built on PoF approach.

## 3 Contributions

This section first presents three context-aware collaborator recommendation algorithms that are developed based on a collaboration context ontology and an ontology-based semantic similarity. Then a public dataset of scientific collaborations is applied in two types of experiments to test and analyze the performances of these algorithms in terms of accuracy and time efficiency.

### 3.1 Context-aware collaborator recommendation algorithms

The collaboration context ontology MCC [12] employs a subject and its involved semantic 3-uples (i.e., <Subject, Predicate, Object>) to define a collaboration and its context. Specifically, a subject indicates a particular collaboration,

while the related predicates and objects refer to its context which is represented by different dimensions. Thus, a collaboration $c$ and its context are considered as a collection of semantic 3-uples with a single subject $c$ in MCC.

Within such collections of semantic 3-uples, an ontology-based semantic similarity was proposed to measure the closeness between two collections [13], which respectively represent two collaborations ($c$ and $d$) and their contexts. This semantic similarity is calculated by the following equation [13]:[5]

$$S(d,c) = \sum_{i=1}^{I} S_1^i(d,c) + \sum_{j=1}^{J} S_2^j(d,c) \tag{3}$$

where $I$ represents the number of dimensions that contain qualitative objects; $J$ represents the number of dimensions that contain quantitative objects; $I + J = T$, $T$ represents the maximum number of dimensions that the context of the collaboration $c$ can contain. Besides, $S(d,c) \in [0,1]$. Smaller $S(d,c)$ implies greater difference between $c$ and $d$.

Based on the semantic similarity $S(d,c)$ and two context-aware recommendation approaches (i.e., PreF and PoF), three context-aware collaborator recommendation algorithms can be developed: PreF1, PoF1, and PoF2. Particularly, PreF1 and PoF2 are already explained in [13]. Thus, this paper only introduces PoF1 algorithm (see Algorithm 1) and differences among the three algorithms (see Fig. 2). It first utilizes a technique of 2D recommendation approaches to predict users' unknown ratings for collaborators (line 1-3). Then, it computes ontology-based semantic similarities between the collaboration $c$ and other collaborations $d$ ($d \in X, d \neq c$), and a sum of semantic similarities between the collaboration $c$ and the recent $K$ collaborations that collaborator $i$ ($i \neq u$) participated (line 6-13). Next, users' adjusted ratings for collaborators are computed according to predicted ratings, calculated semantic similarities, and their weights $w_s, w_r$ (line 4-5, 14-21). Finally, the top $K$ collaborators with higher adjusted ratings will be recommended to the user $u$ (line 22).

PreF1 [13] first pre-processes the collaboration context by means of semantic similarity, then generates 2D collaborator recommendations, and finally produce context-aware collaborator recommendations (see Fig. 2). As for PoF1 (see Algorithm 1) and PoF2 [13], they generate 2D collaborator recommendations, then process the collaboration context using semantic similarity, and eventually produce context-aware collaborator recommendations (see Fig. 2). The differences between PoF1 and PoF2 are on how to apply semantic similarity in filtering or adjusting the the order of collaborators $i$ ($i \neq u, i \notin O^{c,Col}$).

[5] The detailed equations of $S_1^i(d,c)$ and $S_2^j(d,c)$ are available in [13]. This paper do not discuss how to calculate $S_1^i(d,c)$ and $S_2^j(d,c)$.

**Algorithm 1:** PoF1 algorithm.

**Input:** The rating matrix: $R$,
the user: $u$,
the collaboration: $c$,
the set of members in the collaboration $c$: $O^c_{Col}$,
the number of recommendations: $K$,
the number of known collaborations: $|X|$,
the number of users: $m$,
the weight of semantic similarity in adjusted ratings: $w_s$,
the weight of predicted rating in adjusted ratings: $w_r$,
the number of dimensions that contain qualitative objects: $I$,
the number of dimensions that contain quantitative objects: $J$.
**Initialize:** Two lists with zeros: $SC$ (of length $|X|$) and $VU$ (of length $m$).

```
for h ∈ {1,2,..,m} AND k ∈ {1,2,..,m} do
    if R_hk is unknown then
        apply techniques of 2D recommendation approaches to predict
          unknown ratings R_hk;
        if h == u then
            VU(k) ← 1;
for d ∈ {1,2,..,|X|} do
    if d == c then
        S(d,c) ← 0 ;
    else
        S(d,c) ← Σ_{i=1}^{I} S_1^i(d,c) + Σ_{j=1}^{J} S_2^j(d,c);
    while i ∈ O^{c,Col} do
        if collaboration y belongs to collaborator i's rencent K collaborations
          then
            SC(i).insert(S(d,c));
for k ∈ {1,2,..,m} do
    for d ∈ {1,2,..,length(SC)} do
        if k ∉ O^{c,Col} then
            VU(k) ← 1;
for k ∈ {1,2,..,m} do
    if k ∉ O^{c,Col} then
        if VU(k) == 1 then
            R̂(k) ← w_s * sum(SC(k)) + w_r * R_uk;
Rank R̂ in decreasing order and get K highest ratings;
```

**Output:** User $u$'s adjusted ratings $\widehat{R}$, $K$ collaborators with $K$ highest ratings.

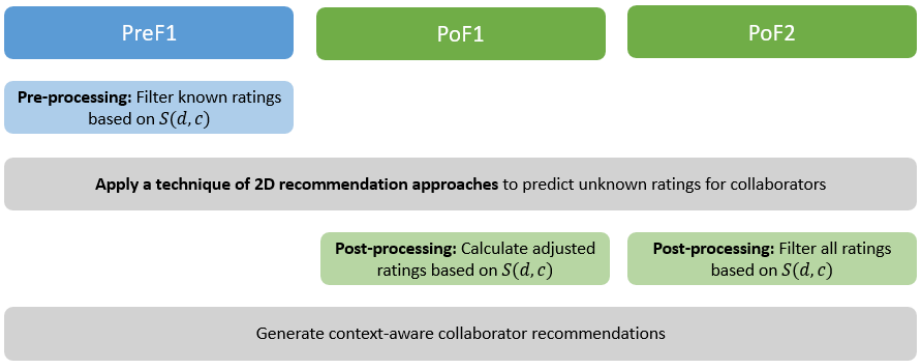


**Fig. 2.** Main steps in PreF1, PoF1, and PoF2.

Using the three algorithms (i.e., PreF1, PoF1, and PoF2), context-aware collaborator recommendations can be produced for users. Specifically, all these algorithms can employ the same technique of 2D recommendation approaches and our proposed ontology-based semantic similarity [13], which makes it possible to test, compare, and analyze their performances through experiments.

### 3.2 Experiments

**Dataset & Evaluation methods** To test and evaluate the performances of PreF1, PoF1, and PoF2, we apply an academic publication dataset[6] [24]. It includes academic articles and their citation relationships until 2019-05-05, which are extracted from DBLP, MAG, and AMiner. All these articles are organized in a non-mutually exclusive hierarchy with 20 top-level domains[7]. This allows us to separate the dataset into 20 blocks. Each block contain articles in a top-level domain.

Particularly, each article in a block represents the fact that its authors have collaborated once in a top-level domain. During such a collaboration, the authors work together to write the corresponding article. This implies that an academic article can be considered as a scientific collaboration. Thus, the side information of an article belongs to the context of a scientific collaboration. Accordingly, each block of articles can be considered as a set of scientific collaborations with their contexts in the corresponding top-level domain.

Specifically, every set is composed of 1000 articles selected randomly from a block due to the different article numbers in these blocks. These articles are arbitrarily divided into two parts, representing separately training collaboration

[6] This dataset can downloaded from https://www.aminer.org/citation.

[7] These domains are Art, Biology, Business, Chemistry, Computer science, Economics, Engineering, Environmental science, Geography, Geology, History, Materials science, Mathematics, Medicine, Philosophy, Physics, Political science, Psychology, Sociology, and Others.

and testing collaborations. Particularly in the three context-aware collaborator recommendation algorithms (i.e., PreF1, PoF1, and PoF2), training collaborations constitute the set $X$, providing known information (e.g., known ratings). Meanwhile, each testing collaboration is $c$. For every author $u$ in a testing collaboration $c$, context-aware collaborator recommendations are generated and analyzed in our experiments.

Particularly, for all scientific collaborations, we have $T = 7$, $I = 1$, and $J = 6$. Therefore, based on Eq. 3, the ontology-based semantic similarity between two scientific collaborations ($c$ and $d$)[8] is:

$$S(d, c) = S_1(d, c) + \sum_{j=1}^{6} S_2^j(d, c) \tag{4}$$

Within this semantic similarity $S(d, c)$, we can conduct experiments to analyze the performances of PreF1, PoF1, and PoF2 in terms of accuracy and time efficiency. To this end, we employ three metrics: F1 [8], Mean Absolute Error (MAE) [26], and execution time. Particularly, a higher value of F1[9] and/or a lower value of MAE[10] indicates more accurate recommendations. As for time efficiency, we measure the execution time[11] that each algorithm takes to generate context-aware collaborator recommendations for an author $u$ in a testing collaboration $c$. Lower execution time represents higher time efficiency.

With the three metrics (i.e., F1, MAE, and execution time), two types of experiments are carried out: experiment with different semantic similarities and experiment with different 2D recommendation techniques.

**Experiment with different semantic similarities** In this experiment, we change the semantic similarity applied in PreF1, PoF1, and PoF2. This provides us an opportunity to investigate how much our semantic similarity [13] contributes to generating context-aware collaborator recommendations. Particularly, our semantic similarity is inspired and developed by other types of semantic similarities [13]. Thus, we need to utilize existing semantic similarities of these types in PreF1, PoF1, and PoF2. Specifically, our experiments involves 5 existing semantic similarities, including Jaccard, Dice, Tversky, TF-IDF, and IC[12] [22].

Each experiment uses a different semantic similarity in a set of scientific collaborations. To analyze their performances in the algorithms, F1, MAE and execution time are employed. All the results are shown in Fig. 3, 4, and 5.

[8] Here, $c$ is a testing collaboration; $|X|$ represents the number of training collaborations; $d(d \in X, d \neq c)$ is a training collaboration.

[9] The range of F1 is $[0, 1]$.

[10] The range of MAE is $[0, +\infty)$.

[11] In our experiments, execution time is counted in milliseconds.

[12] Here, IC represents $IC(c) = -\log p(c)$, where $p(c)$ is the probability of $c$'s appearance in an ontology [22].

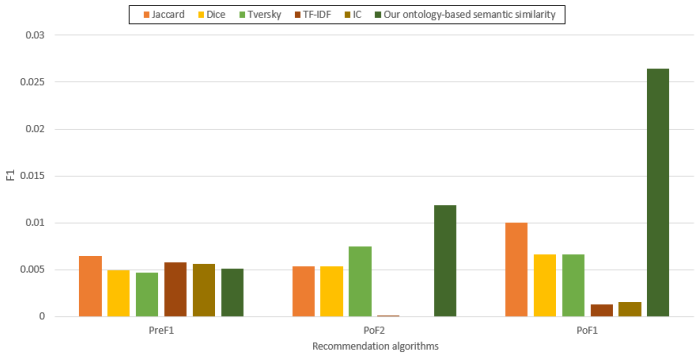


**Fig. 3.** F1 with different semantic similarities in a set of scientific collaborations.

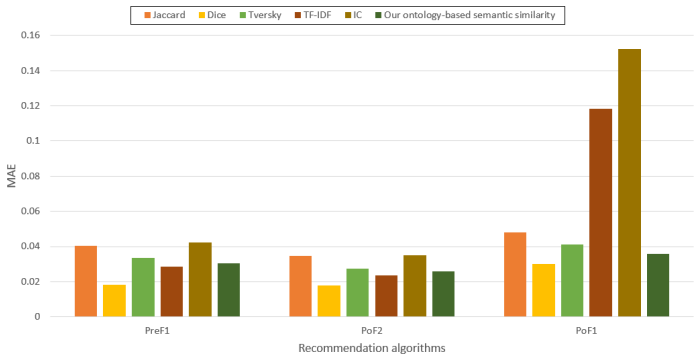


**Fig. 4.** MAE with different semantic similarities in a set of scientific collaborations.

In Fig. 3, our semantic similarity leads to the highest value of F1 when applied in PoF1 and PoF2. This indicates that our semantic similarity can enhance F1 and thus generate more accurate context-aware collaborator recommendations. But it only achieve a medium value of F1 in PreF1. These varied values of F1 imply that the enhancing effect of our semantic similarity depends on the recommendation algorithms, which is driven by the different processing steps of semantic similarities in the algorithms (see Fig. 2).

Besides, when employing our semantic similarity in the algorithms, their MAE results are always lower than those of Jaccard, Tversky, and IC. However, compared to Dice and TF-IDF, our semantic similarity produces slightly higher MAE results (except TF-IDF in PoF1). Considering that our semantic similarity brings significantly better results than Dice and TF-IDF in terms of F1, it is fair to conclude that our ontology-based semantic similarity can improve the

accuracy of PoF1 and PoF2. When implemented in PreF1, our ontology-based semantic similarity has an average performance of accuracy, which is acceptable.

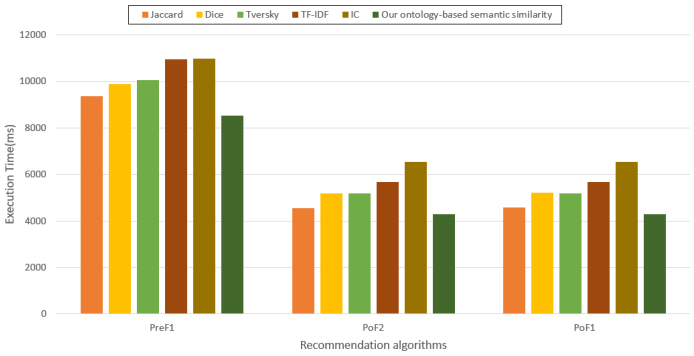


**Fig. 5.** Execution time with different semantic similarities in a set of scientific collaborations.

Lastly, our semantic similarity evidently achieves the shortest execution time among all semantic similarities. This indicates that the time efficiencies of PreF1, PoF1, and PoF2 are augmented through the use of our semantic similarity.

**Experiment with different 2D recommendation techniques** In this experiment, we employ two 2D recommendation techniques in the three context-aware collaborator recommendation algorithms: Neural network-based Collaborative Filtering (NCF) [9] and Probabilistic Matrix Factorization (PMF) [17]. Both techniques belongs to CF approach (cf. Section 2.1). Applying the two techniques in PreF1, PoF1, and PoF2 gives us a chance to explore whether applying our semantic similarity with different 2D recommendation techniques can influence the performances of the three algorithms. Similarly, the accuracy and time efficiency are also evaluated through the three metrics: F1, MAE and execution time. All the results are shown in Fig. 6, 7, and 8.

In summary, when either PMF or NCF is applied in PreF1, PoF2 and PoF1, all values of F1 are higher than those of PMF and NCF themselves (represented as NCF/PMF in Fig. 6, 7, and 8). This indicates that our semantic similarity can increase F1 of PreF1, PoF2 and PoF1 whatever 2D recommendation technique is used. However, F1 values with NCF are much higher than those with PMF. This implies that the enhancement of F1 driven by our semantic similarity relates to the techniques used to generate 2D collaborator recommendations. Between NCF and PMF, our semantic similarity can attain greater F1 with NCF.

Meanwhile, compared with NCF/PMF, lower MAE are also reached when applying PMF and NCF in PreF1, PoF2 and PoF1 (except PMF in PoF1). This signifies that our semantic similarity, while using either PMF or NCF in the algorithms, can reduce values of MAE. Similarly, the decreased MAE values

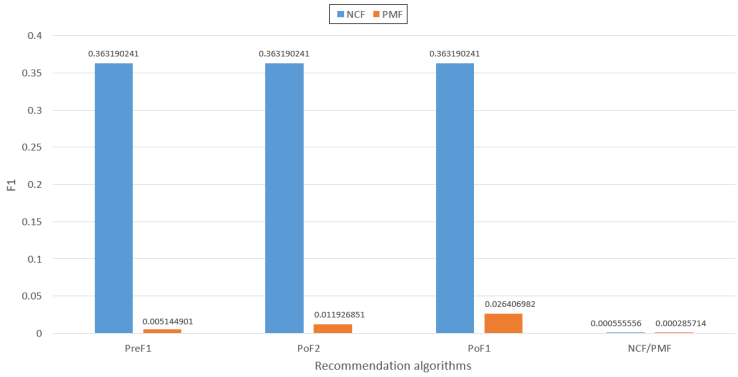


**Fig. 6.** F1 with different 2D recommendation techniques in a set of scientific collaborations.

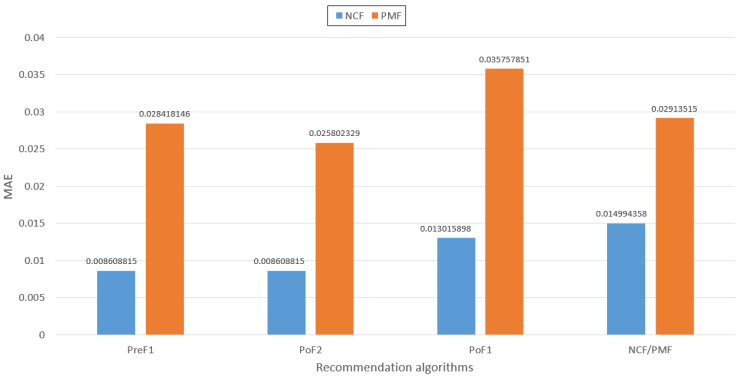


**Fig. 7.** MAE with different 2D recommendation techniques in a set of scientific collaborations.

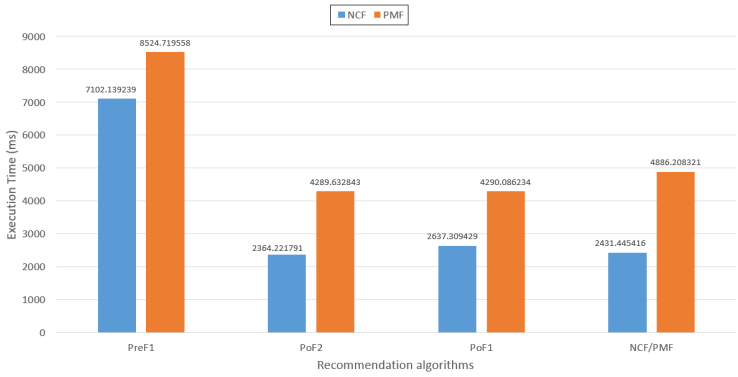


**Fig. 8.** Execution time with different 2D recommendation techniques in a set of scientific collaborations.

with NCF are larger than those with PMF. This also means that the reduction of MAE is caused by our semantic similarity but linked to the techniques used to generate 2D collaborator recommendations. Both higher F1 and lower MAE suggest that our semantic similarity improves the accuracy of PreF1, PoF2, and PoF1. Only its enhancements are more evident with NCF than with PMF.

As for execution time, the results of PoF2, PoF1, and NCF/PMF are very near. On the contrary, the execution time of PreF1 is much longer than those of other algorithms, indicating a higher time complexity of PreF1.

## 4 Discussion

Utilizing a dataset of scientific collaborations, we conduct two types of experiments to analyze the performance of three context-aware collaborator recommendations algorithms (i.e., PreF1, PoF1, and PoF2) from two aspects: accuracy and time efficiency. Based on the results, the following can be concluded:

- Our ontology-based semantic similarity [13] can lead to better time efficiency of PreF1, PoF1, and PoF2. It also leads to higher accuracy in PoF1 and PoF2, but shows no improvement of accuracy in PreF1.
- Calculating our ontology-based semantic similarity in PreF1, PoF1, and PoF2 can produce more accurate context-aware collaborator recommendations, regardless of the applied 2D recommendation technique. However, it positive effect on time efficiency isn't very obvious.

The above summary signifies that with our ontology-based semantic similarity, PreF1, PoF1, and PoF2 algorithms can enhance their performances, either in terms of accuracy or time efficiency, or both. The differences in improvement may be caused by the order of processing our semantic similarity in the algorithms, which deserves further investigation.

Besides, our ontology-based semantic similarity enables us to deal with the collaboration context in the context-aware collaborator recommendation generation processes. This type of context is never considered or discussed in previous studies on such recommendations. These previous studies usually focus on either user context (e.g., [14]) or item context (e.g., [27]). None of the previous studies takes into account users and items together. With the collaboration context, users and items are considered jointly in collaborations. This deepens the comprehension of both users and items in context-aware collaborator recommendations.

Also, this work has some limitations. The recommendations produced by PreF1 and PoF2 [13] may have a serendipity problem [5]: the recommended collaborators are not 'surprising' to users. This leads to insufficient diversity of recommendations: it is often the same collaborators that are recommended to users. Based on PreF1 and PoF2 [13], each collaborator recommended to the user must have involved in collaborations with high similarities. Such collaborators are obvious to facilitate users' collaborations, but not the good ones. The collaborators have not involved in the same collaborations with the user should also be included, which may result in surprising and diverse recommendations.

## 5 Conclusion & Future Work

In this paper, we focus on how to analyze the performances of three context-aware collaborator recommendation algorithms. To solve this issue, two types of experiments are effected in a dataset of scientific collaborations and analyzed in terms of accuracy and time efficiency.

Based on the literature review, we decided to follow PreF and PoF approaches for developing three corresponding context-aware collaborator algorithms: PreF1, PoF1, and PoF2. We then presented how the three algorithms can be used to generate context-aware collaborator recommendations based on a collaboration context ontology and an ontology-based semantic similarity. Finally, a public dataset of scientific collaborations was applied in two types of experiments to test and analyze the performances of the three algorithms through three metrics (i.e., F1, mean absolute error and execution time). The first two metrics serve to evaluate the accuracy of the three algorithms, while the last one aims to measure the time efficiency.

Our future work is to improve and enrich the experiments of the three algorithms. This may helps us to ananlyze why applying a same semantic similarity in the algorithms can result in different improvements.

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