TEMPORAL INFLUENCE IN COLLABORATORS RECOMMENDATION ON SOCIAL NETWORKS

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ABSTRACT

In the last decade, defining recommendations considering Social Networks has been the focus of many studies. Such studies propose new techniques for optimizing different aspects such as the user profile generation and maintenance, the recommendation function and the user connections. Many of those consider mostly the connections established within the social networks, disregarding the rich information that can be extracted from them. In this work, we propose an overall function for recommending collaborations based on a co-authorship Social Network. These collaborations are evaluated and weighted through temporal analysis on co-author relationships. Experiments show that considering temporal aspects can lead to improvements in the ordering of recommendation results. Moreover, this can be used to reduce the number of relationships considered to generate the recommendations.

KEYWORDS

Recommender Systems, Social Networks, Co-Author Social Networks, Measurement.

1. INTRODUCTION

The rapid expansion of Web 2.0 reflects in widespread use of applications with social aspects, including Web-based communities and Social Networks. Recommender systems (recommend items that are likely to be of interest to its users) have followed this trend and many started to consider such a "social context" of users in order to improve their techniques. For example, different approaches take advantage of the social context to improve the recommendation of movies (Golbeck and Hendler 2006) and papers (Hwang et al. 2010).

Furthermore, the focus of recommendation has expanded from information items to individuals in Social Networks. Most of such systems aim to recommend experts and new collaborations in generic networks. For instance, many approaches emerged for recommending possible friends. In those approaches, the systems may define recommendations based on social relations (of friendship) between users who are in social closeness (Chen et al. 2009) or physical proximity (Quercia and Capra 2009).

Given the complexity of recommender systems (which define input and output mechanisms for the recommendation function), much research focus on optimizing different aspects such as the user profile generation and maintenance, the recommendation function and the user connections (Perugini et al. 2004). Many approaches consider mostly the connections established within the social networks, disregarding the rich information that can be extracted from them. An important, and so far unexplored, facet to be considered in this context is the temporal aspects of the connections.

In this context, our work presents, for the first time, different ways to consider temporal aspects in the weighting of relationships in a social network (SN) (which will be used as base for recommending connections). The contributions are summarized as follows. We introduce a procedure for creating a co-authorship social network with weighted relations (Section 3.1). We present a score method for defining academic social closeness (Section 3.2) and propose a new way that includes temporal aspects for defining the weight of relations within the social network (Section 3.3). We use a real dataset to construct a co-authorship network (Section 4.1). Then, we evaluate the quality of our recommendations and the results show

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the improvements obtained by considering the temporal aspects. The results also show that it is possible to obtain good recommendation even when reducing the number of relationships (Section 4.2).

2. RELATED WORK

This section overviews the related work on Social-based recommender systems as well as other work in social networks that regard temporal issues. Most recommender approaches that use social networks consider some structural aspects to generate recommendations. Measures originated in the graph theory are employed to establish scores that estimate the *proximity* between the actors (modeled by a SN) and even to predict new links (Newman 2003, Liben-Nowell and Kleinberg 2007, Quercia and Capra 2009). A detailed study on using different methods to link prediction in social networks is presented in (Liben-Nowell and Kleinberg 2007). However, this work does not explore weighting methods and the impact of these in the score results.

There is a plethora of recommender systems that usually work within a distinct domain. Our work focuses on recommending collaborators within the academic context. Previous approaches closer to ours include those that recommend experts (Kautz et al. 1997, McDonald 2003). In academic social network (co-authorship networks), the network may be unweighted (Liben-Nowell and Kleinberg 2007, Kautz et al. 1997, McDonald 2003). On the other hand, for a weighted network, the *Jaccard Coefficient* is usually applied for the weights (Aleman-Meza et al. 2006, Hwang et al. 2010). Here, we go one step forward and, for the first time, explore the influence of temporal aspects in the weights that determine the recommendation results.

Recent proposals have addressed the importance of consider temporal aspects in recommending items within a social context. For example, Hwang et al. (2010) propose a task-focused approach to recommend literature and consider temporal information (from usage log) for composing a task-based profile. Hence, the temporal aspects are treated in the level of the user profile generation. For Social Networks Analysis (not to recommendation purposes), Tang et al. (2009) propose new temporal distance metrics to quantify and compare the speed (delay) of information diffusion processes considering the evolution of a network. Xiang et al. (2010) present a temporal recommendation approach considering long- and short-term preferences of the users. This approach deals with the changes of preferences over time. However, the focus of such recommendation is items, not individuals or collaborators. Therefore, we can say that our work is the first to study the temporal aspects influence in collaborations recommendation for academic Social Networks.

3. RECOMMENDING COLLABORATIONS

Social Networks are based on the relationship's importance between interaction units. The interaction units are called *actors* and the relationships between them *relational ties* (Newman 2003). Each relational tie may be assigned to a weight measure, which defines the importance of a relationship between its actors. Determining such relationships' weights is a great challenge and is closely related to the type of data the network models. In this paper, specifically, we analyze a scientific collaboration (social) network. In such networks, two scientists are considered connected if they have co-authored a paper, which then seems a reasonable definition of scientific acquaintance (Newman 2003).

In general, the Social Network (SN) of co-author relationships is a pair: $SN=(R,E)$, where R and E are the set of nodes and edges, respectively. Each edge $e \in E$ is a tuple of the form $<r_i, r_j, w_{ij}>$, where the edge is directed from r_i to r_j, and w_{ij} denotes the weight of the association. The weight aims to represent the *proximity* between two authors, where the higher the proximity, the higher its weight.

3.1 Recommendation Function

Based on the aforementioned SN, given a target user r_t and a list of researchers R, a *recommendation function* returns a ranked list of individuals $r_i \in R$ such that a collaboration between r_t and r_i is positively indicated. Figure 1 describes the general function for recommending collaborators, including the SN generation steps (lines 1-9) and the recommendation process (lines 10-17).

Given a list of researchers and a target user of this list, it gets the list of those researchers' publications (line 2). The next step is to match their names to the list of authors in all publications, looking for their co-authorship relations (line 3). For each co-author of the target user (line 4), the function calculates the weight that represents the collaborations intensity between that pair (line 5). The list of researchers and their co-authorships (including the weight of relations) defines the social network *SN* (line 6), which in turn is analyzed to generate recommendations (lines 10-17). Considering the target user, a score function between he/she and all possible researchers to be recommended is calculated (line 11). When such a score function returns a positive value (line 12), this researcher is included in the list of recommendations for the target user (line 13). Finally, the function outputs a ranked list of collaboration recommendations (lines 16-17).

In this scenario, two challenges arise and are the focus of our work: determining the relationships' weighting between actors (line 5) and choosing an adequate score function to order the results (line 11). Here we also analyze the influence of temporal aspects in the recommendation of collaborators. Hence, we propose metrics to weighting relational ties that consider the temporal aspects of collaborations next.

```
Function Collaborators Recommendation
Input: A list of researchers R, a target user r_t ∈ R
 1.  for all r_i ∈ R do
 2.    P_i = Get the list of publications of r_i
 3.    C_i = Find the co-authorships of r_i within P_i
 4.    for all r_j ∈ C_i do
 5.      w_i,j = Calculate the weight w between researchers r_i and r_j
 6.      E = Include {<r_i, r_j, w_ij>} in the list of edges E
 7.    end for
 8.  end for
 9.  SN = Materialize the social network SN(R,E) with weights w
10.  for all r_i ∈ R do
11.    s_ti = Calculate the score s between researchers r_t and r_i
12.    if s_ti > 0 then
13.      Rec_t = Include <r_i,s_ti> in the list of recommendations of r_t
14.    end if
15.  end for
16.  Rec_t = Ordered Rec_t by score values s
17.  return Rec_t
```

Figure 1. Function for recommendation of collaborators

3.2 Score Methods

Traditionally, a recommendation function that considers structural aspects of a SN aims to establish a level of *social closeness* between its individuals. Such a task often uses measures from graph theory that can be handled to indicate new connections (*link prediction*) and academic collaborations (in our case). Typically, link prediction methods assign a *score(x,y)* for all pairs of nodes *<x,y>* within the social network graph, and produce a ranked list in (decreasing or ascending) order of *score(x,y)* (Cherkassky et al. 1996, Newman 2003, Liben-Nowell and Kleinberg 2007, Quercia and Capra 2009).

Nonetheless, our work explores metrics that include temporal aspects in order to determine weights in a SN. Any of the previous methods that determine a *score* to quantify the *social closeness*, which consider only the structural aspects of SN, can be applied here. However, such methods need to be adapted to consider a weighted network. In the context of academic work, the closeness within a group provides evidences of collaborative work trends through a chain of interpersonal connections (within the network). Therefore, a proper method for defining closeness must be used.

Therefore, we consider the *shortest path* method, which is used in graph theory to find a path between two vertices (or nodes) such that the sum of the weights of its constituent edges is minimized. We chose this method because such a function is more adequate to deal with incomplete network. Note that unless we have access to all publications of the researchers (Line 2 of Figure 1), the case of an incomplete network is the most probable to happen. Finally, other approaches can be more depreciated in this situation as for example the *common neighbors*, in which one missing relational tie can significantly depreciate the final result.

3.3 Relational Ties Weighting Aspects

In a co-authorship network, the actors are the researchers and the relational ties are the research collaboration between pairs of researchers. Most recommendation approaches do not consider the rich aspects involved in the relational ties. Furthermore, different aspects can be considered for defining the weights of relational ties, and the most common one relates to the quantity of publications. Nonetheless, we also propose alternatives to consider temporal aspects in relational ties' weighting methods.

Publications Aspect. The process of determining the weight *p* for each relational tie within a SN usually considers the quantity of publications of each pair of researchers <*i*, *j*>, as given by Equation 1.

$$p_{ij} = \frac{n_{ij}}{n_i} \tag{1}$$

where n_{ij} denotes the number of common papers between <*i*, *j*> and n_i the number of papers of author *i*. Note that we consider non-symmetric weights, since p_{ij} is different from p_{ji} when n_i is unequal to n_j. This measure is an asymmetric variant of the *Jaccard Coefficient* and has already been applied in the context of Social Networks (Aleman-Meza et al. 2006, Hwang et al. 2010), either as symmetric or asymmetric variant.

Novel Temporal Aspects-based Weight. To the best of our knowledge, this is the first work that considers the influence of temporal aspects while determining the relational weights in a SN that is the base for recommending academic collaborations. The temporal aspects relate to the publication year of the papers that were considered in the SN construction. The year values are used to infer how recent the collaborations among researchers are. This way, we can define higher values to relationship that were active more recently.

Equation 2 presents the temporal aspect factor that is later considered within the weights.

$$t_k = \begin{cases} \dfrac{w-(y_r - y_k)}{w} & \text{, if } (y_r - y_k) > w \\ t_{\min} & \text{, otherwise} \end{cases} \tag{2}$$

where *w* is the time interval to be depreciated proportionally (from the more recent publication year to the last year, which is depreciated), y_r denotes the more recent publication considered in the SN construction, y_k denotes the publication year to which the temporal factor is calculated, and t_{min} is the minimum value of t_k that can be generated and applied to years whose differences to y_r are greater than *w*.

Now, we propose two different weights that consider such temporal aspects. The first weight, called *Tr*, applies the temporal factor to the most recent publication year of two authors. This weight aims to define higher values to relationships that were active recently. Equation 3 presents its formula.

$$Tr_{ij} = p_{ij}.t_{y_{ij}} \tag{3}$$

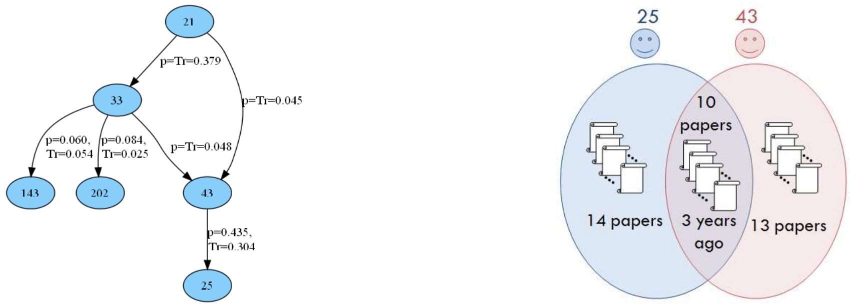
where p_{ij} denotes the weight considering publications quantity and t_{yij} indicates the most recent publication year of the pair of the researchers <*i, j*>.

The second weight, called *Tg*, applies the temporal factor considering all co-authored publications. Here, p_{ij} is modified to consider the temporal factor for calculating both numerator and denominator. The publication year is regarded in the equation for all publications. This weight aims to define high values to relationships that were activate more times recently and is given by Equation 4.

$$Tg_{ij} = \frac{\sum_{k=1}^{n_{ij}} t_{y_k}}{\sum_{x=1}^{n_i} t_{y_x}} \tag{4}$$

where n_{ij} denotes the number of common papers between <*i*, *j*>, n_i the number of papers of author *i*, and *t* the temporal factor being evaluated according to each year of publication being considered.

As an example, consider the network presented in Figure 2a for user *21*, who is also the target user of the recommendation function. For simplicity, Figure 2a shows the weights in only one direction with values using methods *p* (Equation 1) and *Tr* (Equation 3). The weights between the researchers' pairs <21,33>, <21,43> and <33,43> are the same using both methods. This case indicates that such pairs co-authored papers in the most recent year considered (y_r parameter of temporal factor). In the other cases, the weights suffer temporal depreciation. For instance, the collaboration behavior for the pair <43,25> is illustrated in Figure 2b. Note that, for this pair, there was a reduction comparing the weight value *p* and *Tr*. Specifically, the value of $p_{43,35}$ is approximately 0.435 (total of co-authored papers by these authors divided by the total number of publications of author 43, i.e., 10/23). However, for calculating *Tr*, this value of *p* is depreciated using $t_{y43,35}$. In this example, the parameter *w* (representing a time window for depreciation) used is equals to 10. The difference between most recent year and year of most recent publication co-authored by pair <43,25> is 3 years ago. The obtained factor temporal corresponds to 0.7. (i.e. (10-3)/10). Then, the final value of *Tr* is approximately 0.304 (i.e, $p_{43,35}$* $t_{y43,35}$ = 0.435*0.7). We consider these weights with temporal aspects to find recommendations to user. So, a score method must be applied, considering these weights, to rank the results. In this case, as our weights represent the "proximity" between users, each final weight to be used to *shortest path* method must be calculated as: ∞, if "proximity" weight value equals to 0 (researchers not connected); 1 minus the "proximity" weight value, otherwise. For ranking the recommendation results, the researchers directly connected are discarded (not recommended) and the remainder output of *shortest path* score method must be ascending ordered (as lower the result value is as in more *social closeness* the researchers are).



(a) partial network (b) common publications

Figure 2. Example of defining the weights within a partial Social Network

4. EVALUATION STUDY

This evaluation study aims to consider different weights and evaluate the influence of temporal aspects in collaborations recommendation on Social Networks, more precisely in a Co-Authorship SN. The dataset used in the construction of studied networks is described in Section 4.1 and the evaluation results in Section 4.2.

4.1 Dataset Description

The dataset includes researchers of 20 Brazilian PhD programs in Computer Science (COPPE/UFRJ, PUC/PR, PUC/RIO, PUC/RS, UFAM, UFBA, UFC, UFCG, UFF, UFMG, UFPE, UFPR, UFRGS, UFRJ, UFRN, UFSCAR, UNB, UNICAMP, USP and USP/SC) and their publications. In total, we have considered 650 researchers (i.e., the faculty members of those PhD programs). Their publication data was extracted from DBLP (http://www.informatik.uni-trier.de/~ley/db) on August 03, 2010. We considered only the papers published in conference proceedings or in journals (i.e, we do not consider the other types of publications such as thesis, books and book chapters) in order to specify the co-author relations among the researchers.

Note that recent studies (Laender et al. 2008, Reitz and Hoffmann 2010) discuss the coverage of Computer Science sub-fields by DBLP. Such coverage has reached the approximate value of 67%, covering up to 96% of some sub-fields. Nonetheless, DBLP is widely applied to obtain Computer Science publications (even though some exception results can be justified by the limited coverage of a specific sub-field).

Regarding timeline, two time intervals are used in the experiments: until 2007 and until 2010. Such interval relates to the year of the publications considered to building the (co-authorship) social network. These time intervals show the evolution of the network for a period of approximately 2.5 years.

Two SNs formed by the researchers of the Brazilian PhD Computer Science programs are then constructed using the aforementioned time intervals. With 650 actors (researchers), if all of them collaborated, the number of pairs of relational ties (2 links between two authors) in the SN would be 210,925. Nonetheless, the SNs corresponding to both datasets (until 2007 and until 2010) contain, respectively, 1,086 and 1,333 pairs of relational ties. A comparative between the two SNs indicates that 247 new collaborations (pairs of relational ties) were initiated in that period. In our experiments, such new collaborations were considered relevant and could be considered as the baseline for a recommendation function applied in 2007, because they effectively occurred later. Furthermore, such new collaboration give real evidence that they are interesting to the researchers because publication(s) was(were) obtained as result after 2007. Therefore, a good recommender system would have already recommended them in 2007.

4.2 Evaluation and Results

In order to perform the comparative evaluation, we use all possible recommendations defined by the approaches using the dataset in the first time interval (publications until 2007). We also compared the new co-authorships from the second dataset (until 2010) and the recommendations generated by our system. As ground truth, we considered the real evolution from the 2007 to 2010, i.e., the actual new connections that happened over time are considered the correct result.

The results of experiments are formed by standard evaluation strategies from information retrieval. Specifically, the following metrics were used: average precision (Avg-Prec), mean average precision (MAP), r-precision (R-prec), recall and *Student's t-test* (Baeza-Yates and Ribeiro-Neto 1999). For evaluating the metrics, each user was considered as a query and each collaboration recommendation for that user as a result of that query. A brief explanation about the evaluation metrics associated to our domain is presented below. Precision is the fraction of the recommendations retrieved that are relevant to the users. Average precision is the average of precisions computed at each point of the relevant recommendations in the ranked sequence. MAP is calculated for a set of users is the mean of the average precision scores for each user. R-prec for a set of users is the mean of precisions calculated at top R position in the ranking of results (where R is the number of relevant recommendations for each user). Recall is the fraction of the recommendations that are relevant to the user that are successfully retrieved. *T-test* is a statistical test employed to verify the existence of differences statistically significant.

The goal of this set of experiments is to evaluate the results of the recommendation considering different weighting method for the SN (remember that the score method used is the shortest path). Table 1 lists the methods, the parameters' values and the evaluation results. The weighting methods evaluated in these experiments are as follows.

1. In the first evaluation, no weighting method is used and the relational ties are not valued.
2. The second method is the asymmetric variant of *Jaccard Coefficient* presented in Equation 1.
3. The third method uses only the temporal factor (Eq. 2), using the parameters specified on Table 1.
4. The fourth method is the *Tg* (tested with two different combination of parameters) that considers the temporal factor *globally* using publication year of all papers.
5. The fifth method is the *Tr* (tested with three different combination of parameters) that considers the temporal factor applied using only the most recent year among all co-authored publications years between two researchers.

As Table 1 shows, all methods provide low values of MAP and R-prec. This probably happens because the recommendations were not evaluated by the users and only the new collaborations emerged in the evaluated period (2008-2010) are considered relevant. The MAP results of the best method not considering temporal aspects (method 2) and of all methods using temporal aspects show that there is no statistically significant difference on using *T-test* with significance level of 0.05. This probably occurs because the same score function (*shortest path*) is being used in all cases. Then, the same relevant recommendations are being returned by most methods, and the difference is only in the ordering of recommendations. The only exception is the method numbered as 5.3 (*Tr* with t_{min}=0.00) in which there is a reduction in the relationships of SN generated, because the researchers with collaborations relationships older than 10 year (*w* value) will not be modeled (value of t_{min}=0).

In this case study, the reduction in the number of SN relations by the use of weighting method 5.3 was approximately 4.24%. Then, the number of SN relations considered by the score method to generate and order recommendations also was reduced. Even with this reduction, the MAP results of the method 5.3 were slightly higher compared to the best method without temporal aspects (method 2). Therefore, we claim that such results shows that temporal aspects can be indeed used to reduce the search space and still obtain results comparable to those without such reduction.

In terms of recall (see Table 1), method 5.3 reduces the recall value of *shortest path* approach from 74.09% to 72.29% with improvements in MAP and R-prec when compared to the methods not using temporal aspects. In this experiment, our SN had already a selection in its relationships (the actors are the set of professors in PhD programs). The existence of old and discontinued collaborations among these professors does not occur as frequent as in other scenarios. For example, collaborations that are discontinued occur more frequently between professors and his students, since some students graduate and stop doing research. In this case, the reduction in the relationships of a SN using temporal aspects can be even more advantageous and lead to more significant improvements in the recommendation results.

Since the temporal aspects did not provide many improvements in terms of MAP, we further analyzed the Avg-prec results for each researcher. An analysis user-by-user verified the cases of considers temporal aspects improved or worsened the results recommendation in terms of Avg-Prec only considering the cases where at least one of methods the two returns relevant collaborations. Table 2 summarizes the results. There were 91 improvements, 58 worsening and 49 unchanged results in Avg-Prec values of users' recommendations. Then, for method 5.1, the improvements by user occurred in 45.96% of cases and the worsening only in 24.75% of this. These results are still better when the temporal aspect with SN reduction is considered (method 5.3). For this, there were 115 improvements, 50 worsening and 33 unchanged results in Avg-Prec values of users' recommendations. Then, for the method 5.3, the improvements by user occurred in 58.08% (majority, more than half) of cases and the worsening only in 16.67% of this. These results appointed indices of improvements in the recommendations results by the consideration of temporal aspects. Table 3 presents the top 5 improvements and worsening of method 5.1 (*Tr*) compared to method 2 (only publications weights). In this table, the top 5 improvements are represented by positive difference values, while top 5 worsening are represented by negative differences. It can be observed that the improvement percentage (in absolute values) was higher that the worsening percentage values.

Table 1. Mean Average Precision, R-Precision and Recall results for the different weighting methods

#	Weighting method	Temporal parameters	MAP	R-prec	Recall
1	Unweighted	Not applied	4.34%	2.51%	74.09%
2	Publications weights	Not applied	6.36%	4.65%	74.09%
3	Only temporal	[y_r=2007, w=10 , t_{min}=0.01]	4.08%	2.65%	74.09%
4.1	Tg	[y_r=2007, w=10 , t_{min}=0.01]	6.59%	4.71%	74.09%
4.2	Tg	[y_r=2007, w=20 , t_{min}=0.01]	6.38%	4.58%	74.09%
5.1	Tr	[y_r=2007, w=10 , t_{min}=0.01]	6.72%	5.03%	74.09%
5.2	Tr	[y_r=2007, w=20 , t_{min}=0.01]	6.55%	4.81%	74.09%
5.3	Tr	[y_r=2007, w=10 , t_{min}=0.00]	6.56%	5.07%	72.29%

Table 2. Comparative considering the users for whose one of the approaches returns some relevant recommendation

	Method 5.1		Method 5.3	
	# users	percentage	# users	percentage
Improvements	91	45.96%	115	58.08%
Worsening	58	29.29%	50	25.25%
Unchanged	49	24.75%	33	16.67%

Table 3. Top five users beneficiated and prejudiced with the use of temporal aspects

# researcher	Method 2 - Avg-Prec	Method 5.1 - Avg-Prec	Difference
2	50.00%	100%	+50.00%
21	23.81%	66.67%	+42.86%
166	16.67%	50.00%	+33.33%
624	18.33%	41.67%	+23.34%
634	12.50%	33.33%	+20.83%
447	50.00%	33.33%	-16.67%
516	35.84%	19.18%	-16.66%
37	28.57%	12.04%	-16.53%
591	33.33%	25.00%	-8.33%
605	14.29%	7.69%	-6.60%

In this case, the recommendations for the user numbered as 2 obtained the high improvement percentage. For example, the second top improvement occurs with user 21. For this user, method 2 returns the relevant recommendations in the positions ranking 3 and 9, while method 5.1 returns the relevant recommendations in positions ranking 1 and 6. Then, the use of temporal aspects improved all recommendations positions in this case. To illustrates, the partial Social Network of Figure 2a represents the network connections used to generate the top-3 recommendations of method 2 for target user 21 (researchers 25, 202 and 143 in this order). However, by the use of method 5.1, the order of these recommendations is modified (researchers 143 at first, 202 at second and 25 only at position twenty five). Among these three researchers, the only considered relevant recommendation to target user 21 is the researcher 143. This researcher, by the use of temporal aspects, was correctly ordered as top 1. One second example, the second top worsening occurs with the user 516. For this user, the method 2 returns the relevant recommendations in the positions ranking 1, 32 and 239; while method 5.1 returns the relevant recommendations in the positions ranking 2, 32 and 235. For this user, the gain in Avg-Prec of method 2 occurs only because the first relevant recommendation is presented in position 1; in the two others recommendations, the method 5.1 has a performance equal or superior. These results are very interesting and they show that consider temporal aspects can lead to improvements in recommendations ordering.

5. CONCLUSION

This paper presented an overall function for recommending collaborations based on a co-authorship Social Network. We proposed different ways to consider temporal aspects in the weighting of collaborations on co-author relationships, which will be used as base for recommending connections. The ultimate goal was to analyze the influence of these weighting methods in recommending academic collaborators. We performed experiments with real dataset that show that considering temporal aspects can lead to improvements in the ordering of recommendation results. Moreover, the results showed that is possible use temporal aspects to reduce the number of relationships considered to generate the recommendations.

As for future work, we plan to study the influence of temporal aspects when using other score functions (link prediction methods). Likewise, the improvements obtained when using temporal aspects can be tested in other social networks, such as those that connect friends.

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