Temporal and Topical Profiles for Expert Finding

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ABSTRACT

We explore the possible advantages of dividing a single heterogeneous profile into several more homogeneous subprofiles for an expert finding task. We consider two different dimensions to perform this division, topical and temporal, and also a combination of both. Topical subprofiles are obtained from a clustering process of the documents associated to each expert, whereas temporal subprofiles are generated by simply dividing the temporal sequence of documents into several parts. The experiments are carried out in the domain of political expert finding, using a dataset of parliamentary documents. The results suggest that, although the two types of subprofiles increase the quality of the recommendations, topical subprofiles and specially the combination of topical and temporal subprofiles get the best results.

KEYWORDS

expert finding, temporal profiles, topical profiles, politics

1 INTRODUCTION

Expert finding systems are a specific kind of recommender systems [7] where the items to be recommended are people. Given a query submitted by a user specifying the problem to be considered, the expert finding system will return an ordered list of possible candidates having the required expertise to tackle this problem [4]. Expert finding systems have many applications (in community question answering, the academic world, industry, social media,...) and there is a growing interest on them [1, 21, 22, 29].

A key point for the operation of an expert finding system is how to learn and how to represent the knowledge/information of the system about the possible candidates. A way of representing the expertise of a candidate is to use a user/expert profile [17]. The most common and simple type of profile associated to a candidate expert is composed of a set of (weighted) terms or keywords describing their areas of interest and expertise [16], although there are also profiles based on semantic networks or concepts [25]. The key advantage of term-based profiles is that these terms can be easily and automatically extracted from the documents associated to the expert, and could be more easily interpreted.

The main goal of this work is to study how the results of an expert recommendation system could be affected by taking into account either the temporal or the topical dimension of data, or both, in the building process of the profiles. For this purpose, we start from a single monolithic profile for each expert, where all terms of the documents associated to this expert are grouped together. Then we want to study whether the division of these single profiles into several subprofiles which are more homogeneous in some sense could improve the quality of the recommendations.

A way of doing this is to make divisions based on the different topics in which an expert can be interested, thus obtaining more homogeneous subprofiles from a topical point of view. We can divide the set of documents associated to an expert, for example using a clustering technique, in order to get subsets of documents topically homogeneous, and then generate a subprofile for each of these subsets.

Another way is to consider groups of documents temporally homogeneous, by dividing the temporal sequence into several parts and then to obtain a (temporal) subprofile for each of these groups. Finally, we could also combine both dimensions, trying to obtain subprofiles simultaneously homogeneous both temporally and topically.

Although the methods to get homogeneous subprofiles proposed in this work to improve the expert finding task can be applied to any domain, the experiments will be carried out with a collection of parliamentary documents, where the experts to be recommended are politicians working in a parliament.

The remainder of this paper is organized as follows: Section 2 briefly discusses some related works. In Section 3 we introduce monolithic profiles and how they can be used by the recommender system. Sections 4 and 5 describe topical and temporal subprofiles, respectively, whereas in Section 6 combined subprofiles are discussed. Section 7 is devoted to the experimental part of the work, including experimental setting, results and discussion. Finally, Section 8 contains the concluding remarks.

2 RELATED WORK

There is an increasing interest about how to include temporal information within recommender systems, although most of the works are focused only on collaborative filtering. One of the basic ideas is to weight the ratings using a decaying factor based on the time gap [15]. The incorporation of time in a latent factor model is also a key factor in the performance of timeSVD++ [20] (the winner of the Netflix prize). An interesting survey of time-aware recommender systems is provided in [9] (also centered in collaborative filtering). In [23] a content-based filter for tweets is studied, where a specific time frame is learned for each user, thus recommending to her only tweets within this personalized frame. Temporal discounting (exponential and hyperbolic) is used in [28], together with an expert finding approach for question routing, in the context of Community Question Answering (CQA) systems.

There are many papers that consider compound profiles instead of monolithic ones, for example using long-term and short-term subprofiles [18], subprofiles based on positively and negatively judged documents [8] or hierarchical profiles (using a fixed taxonomy) [24]. Other methods consider topical (sub)profiles generated using cluster methods: some works group terms or tags (not documents) for profiling in recommender systems [2, 3], whereas other group documents, either for search personalization purposes [11, 26] or for filtering and expert recommendation [14].

We are not aware of any previous work simultaneously dealing with the temporal and topical dimensions of profiles, except [24], which is centered on expert profiling but not on (expert) recommendation.

3 MONOLITHIC PROFILES AND THE RECOMMENDER SYSTEM

Let $E = \{e_1, \ldots, e_r\}$ be the set of candidate experts. Given a candidate expert $e \in E$, we have a set of n_e documents $D^e = \{d_1^e, d_2^e, \ldots, d_{n_e}^e\}$ which are associated to e. These documents in some sense represent (possibly in an implicit way) the interests and expertise of e. For example, in an academic setting the documents could be the scientific articles written by each author or, for lawyers, the court cases they have worked on. In the political setting where we are focusing in this paper, these documents could be the transcriptions of the interventions of politicians in parliamentary sessions.

Given a candidate expert e, the monolithic profile for e is built by simply concatenating all the documents in D^e into a single macro document, $d^e = \cup_{i=1}^{n_e} d_i^e$. The process is illustrated in Figure 1. Then, we have a collection of monolithic documents/profiles $\mathcal{D}^m = \{d^{e_1}, \ldots, d^{e_r}\}$. The recommender system will be obtained from this collection using an information retrieval system (IRS): the profiles collection will be indexed for use by the IRS. When a query representing the expertise required by a user is submitted to the IRS, this will generate a ranking of profiles, and the top-ranked experts will be returned to the user.

4 TOPICAL SUBPROFILES

In order to get subprofiles topically homogeneous, we are going to use a clustering method based on LDA (Latent Dirichlet Allocation) [5]. LDA is a non supervised method which finds latent topics in a document collection and assigns a probability distribution of topics to each document (and also a probability distribution of terms to each topic). LDA needs an input parameter, k, representing the number of topics to be used. In order to use LDA as a clustering method, once LDA has been applied, each document is assigned to the cluster associated to its most probable topic [14], thus obtaining a partition of the document collection into k clusters.

In our case the document collection to be clustered is the one formed by all the documents associated to all the possible experts, $\mathcal{D} = \cup_{i=1}^{r} D^{e_i}$. We do it in this way in order to find a single set of topics common for all the experts. Each cluster, $\mathcal{D}_l$, $l = 1, \ldots, k$, is formed by the documents of the experts which are associated to the l-th topic, x_l (those documents whose most probable topic is x_l), that is to say:

$$\mathcal{D}_l = \{d_i^{e_j} \mid l = \arg\max_{s=1,\ldots,k} p(x_s|d_i^{e_j}),\ j = 1, \ldots, r,\ i = 1, \ldots, n_{e_j}\}. \tag{1}$$

As these clusters contain documents from different experts, a specific local clustering for each expert e and each topic x_l, D_l^e, is obtained by grouping the documents within each global cluster that are associated to the given expert, $D_l^e = \mathcal{D}_l \cap D^e$. Then each expert e will have associated as many subprofiles as local clusters have been generated for her (at most k). These subprofiles are then documents, $d^{e,l}$, which are built by concatenating the documents within each local cluster D_l^e, $d^{e,l} = \cup_{d_i^e \in D_l^e} d_i^e$. Figure 2 illustrates all the process for generating the topical subprofiles.

The recommender system is thus obtained by indexing this subprofile document collection $\mathcal{D}^{tsp}$ and using again an IRS, where

$$\mathcal{D}^{tsp} = \{d^{e_1,1}, \ldots, d^{e_1,k}, d^{e_2,1}, \ldots, d^{e_2,k}, \ldots, d^{e_r,1}, \ldots, d^{e_r,k}\}.$$

However, in this case the result returned by the IRS for a given query is a ranked list of subprofiles (and now there is not a one-to-one association of experts and subprofiles). As we need a ranking of experts, a fusion strategy to combine the scores of the subprofiles associated to the same expert is required, in order to rerank the combined scores and recommend the top-ranked experts. We will use the so-called *CombLgDCS* fusion method [13], which aggregates the scores of all the expert subprofiles but reducing them proportionally to the logarithm of their positions in the ranking.

5 TEMPORAL SUBPROFILES

The other option to divide the monolithic profiles into more homogeneous subprofiles is to use the temporal dimension instead of the topical dimension of the documents. Then we are going to divide the temporal line into h intervals and will group together the documents associated to an expert which belong to the same temporal interval. More formally, let us consider the h temporal intervals I_u, determined by $h + 1$ time points $t_0 < t_1 < \ldots < t_h$, $I_u = [t_{u-1}, t_u)$, $u = 1, \ldots, h$. We define in this case the h global temporal clusters $\mathcal{T}_u$ as follows:

$$\mathcal{T}_u = \{d_i^{e_j} \mid t_{u-1} \le date(d_i^{e_j}) < t_u,\ j = 1, \ldots, r,\ i = 1, \ldots, n_{e_j}\}. \tag{2}$$

Alternatively, we could repeatedly apply clustering only to the documents associated to each expert e, D^e, thus obtaining topics specific for each expert, but we are not going to explore this option in this paper.

Expert e may have less than k local clusters in case that some global clusters do not contain any documents associated to e.

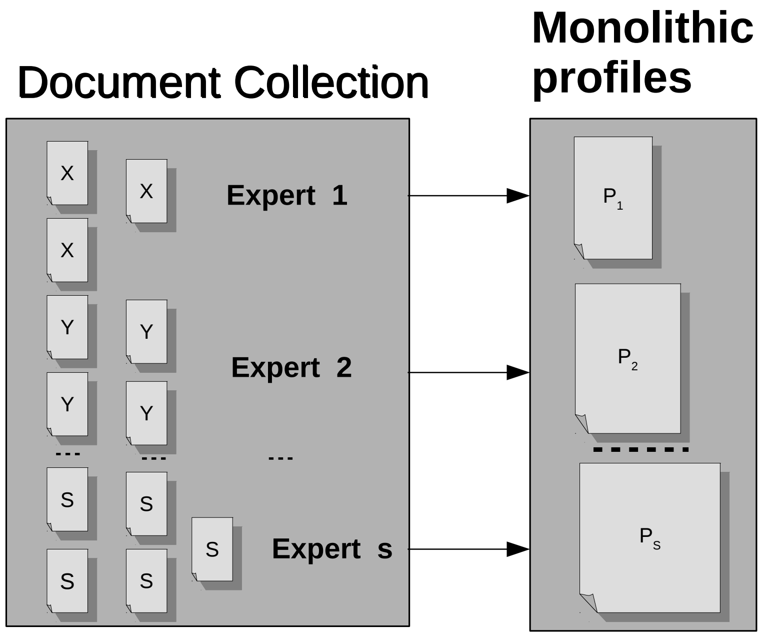

Figure 1: Building the monolithic profiles.

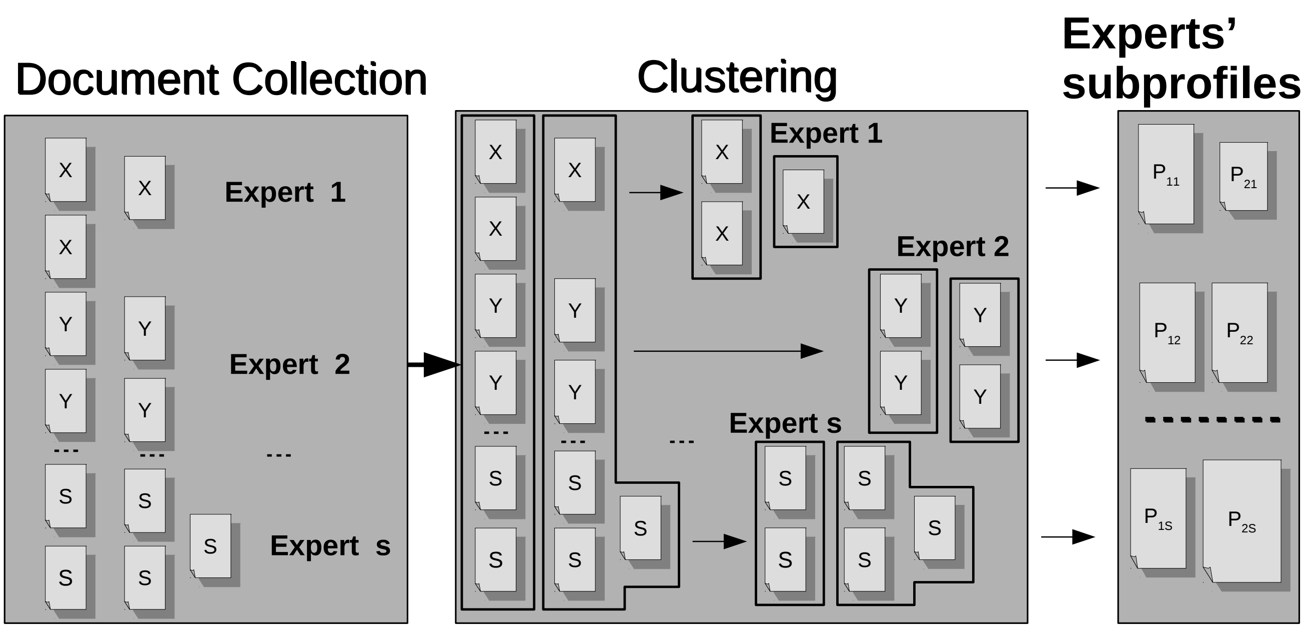

Figure 2: From the document collection to the topical subprofiles using clustering.

where $date(d)$ is a function that returns the date of document d. As in the case of topical clusters, we extract the local temporal clusters for each expert e in the same way, i.e. by grouping the documents within each global temporal cluster which are associated to e, $T_u^e = \mathcal{T}_u \cap D^e$. Also, the (at most h) temporal subprofiles for each expert e are built by concatenating the documents within each

T_u^e, $d^{e,u} = \cup_{d_i^e \in T_u^e} d_i^e$ (i.e. each expert e would be represented by at most h monolithic profiles, one per temporal period), which are then indexed by the IRS. *CombLgDCS* will also be used to obtain a ranking of experts.

6 TEMPORAL AND TOPICAL SUBPROFILES

We can try to combine both the temporal and the topical dimensions in order to obtain subprofiles which are simultaneously topically and temporally homogeneous.

A way of doing this is first to obtain temporal subprofiles and next further subdivide them topically, in order to get sub-subprofiles thematically homogeneous. In this case we would have to cluster separately the documents within each temporal cluster. This would imply to apply LDA to each of the h temporal subcollections of documents (in this way obtaining specific topics for each time period). Another option, which is the one that we are going to use in this paper, is first to carry out the topical division, obtaining topical subprofiles and later to subdivide them temporally. In this way we only have to apply LDA once to the complete document collection.

More precisely, let $\mathcal{D}_l$ as defined in eq.(1), $l = 1, \ldots, k$, and $\mathcal{T}_u$ as defined in eq.(2), $u = 1, \ldots, h$. Then the global topical-temporal clusters, $\mathcal{DT}_{lu}$ are defined as

$$\mathcal{DT}_{lu} = \mathcal{D}_l \cap \mathcal{T}_u, \; l = 1, \ldots, k, \; u = 1, \ldots, h. \tag{3}$$

It should be noticed that the total number of topical-temporal clusters generated can be lesser than the product $k * h$, because some combinations of topics and temporal intervals may be empty (i.e. there are no documents about a given topic at certain time intervals). This process is illustrated in Figure 3, where $k = 6$ topics and $h = 4$ temporal intervals give rise to only 13 topical-temporal clusters.

The local clusters for each expert e are obtained, as in the previous cases, by grouping together the documents within each topical-temporal cluster that are associated to e, i.e. $DT_{lu}^e = \mathcal{DT}_{lu} \cap D^e$. Also, the documents within each local cluster are concatenated and the corresponding macro documents are indexed by the IRS.

7 EXPERIMENTS

7.1 Experimental settings

The experimental work to test our proposals has been carried out in the domain of political expert finding [12, 13]. We have used the Records of Parliamentary Proceedings (in Spanish) from the Andalusian Parliament in its 8th Term of Office (which covers four years of parliamentary activity, from march 2008 to march 2012). These records contain the transcriptions of the speeches of the Members of Parliament (MPs) in the initiatives discussed in committee and plenary sessions. There are a total of 5258 initiatives in this term and 12633 interventions of MPs (which are the experts to be recommended). We randomly partitioned the set of initiatives, using 80% for the training set (to build the subprofiles from the interventions contained in these training initiatives) and 20% for the test set (to obtain the queries), and this sampling process is repeated five times, reporting then the average results of these five partitions.

Available at http://irutai2.ugr.es/ColeccionPA/legislatura8.tgz

Concerning the implementation details of the recommender systems, the base IR system is built using the Lucene library and its default implementation of the Language Model as retrieval model. Previous to indexing the (sub)profiles of each MP, stop words were removed, stemming performed and any remaining terms appearing in fewer than 1% of the interventions were also deleted. For those experiments that require LDA to cluster documents, we used the R implementation (*topicmodels* package), with hyperparameters α and β fixed to $50/k$ and 0.1, respectively (these are the by-default values), where k is the number of topics. For the parameter k, we have tested two classical alternatives in cluster analysis: (a) $k = m * n/t$ [10], where m is the number of terms in the collection ($m = 4,208$), n is the number of documents/interventions in the training set ($n = 10,025$) and t is the number of nonzero entries in the document-term matrix ($t = 1,702,296$). The value of k is then 24. (b) $k = \sqrt{n/2}$ [19], which only considers the number of interventions in the collection. In this case, $k = 70$. With respect to the temporal division, in this case we use $h = 4$ temporal intervals, each one roughly corresponding to one year.

While the interventions within the initiatives in the training set are used to build the (sub)profiles of the MPs, the initiatives in the test set are used to obtain queries and relevance judgments. More precisely, we use the title (which is a short description of the initiative) and its subjects (which are terms from a controlled vocabulary assigned to each initiative by Parliament staff) to simulate a query representing a real expert finding task. If we focus only on the test initiatives corresponding to committee sessions (i.e. excluding initiatives in the test set discussed in plenary sessions, where all the MPs participate, which are more general and political and less specific than those from committees), we have a very simple way of fixing the ground truth to evaluate the different approaches: any MP who is a member of the committee where the initiative generating the query has been discussed is relevant (is a potential expert for this query). There are twenty-six different committees covering different areas (as for example Education, Health, Culture, Environment,...), having on average 15.2 MPs per committee.

We have used three classic IR metrics to measure the performance of the different recommender systems: precision@10, NDCG@10 (normalized discounted cummulative gain), both focusing on the top 10 MPs retrieved and recall@nr, where nr is the total number of relevant MPs for each query. To compute these measures, we have only considered those MPs having at least 10 interventions in the training set (a total of 132 persons).

7.2 Results

We have experimented with four types of profiles: monolithic profiles (MONP), topical subprofiles (TOPS), temporal subprofiles (TEMPS) and topical-temporal subprofiles (TOPTEMPS), as described in the previous sections 3, 4, 5 and 6, respectively. For both TOPS and TOPTEMPS subprofiles we have used the two methods of selecting the number of topics previously described. For TEMPS we fixed the number of temporal intervals to 4. The results are displayed in Table 1. The percentages of improvement of each method

https://lucene.apache.org/

In this case we still have on average 612 test initiatives per partition.

We do not use recall@10 because usually the number of relevant experts for each query is greater than 10.

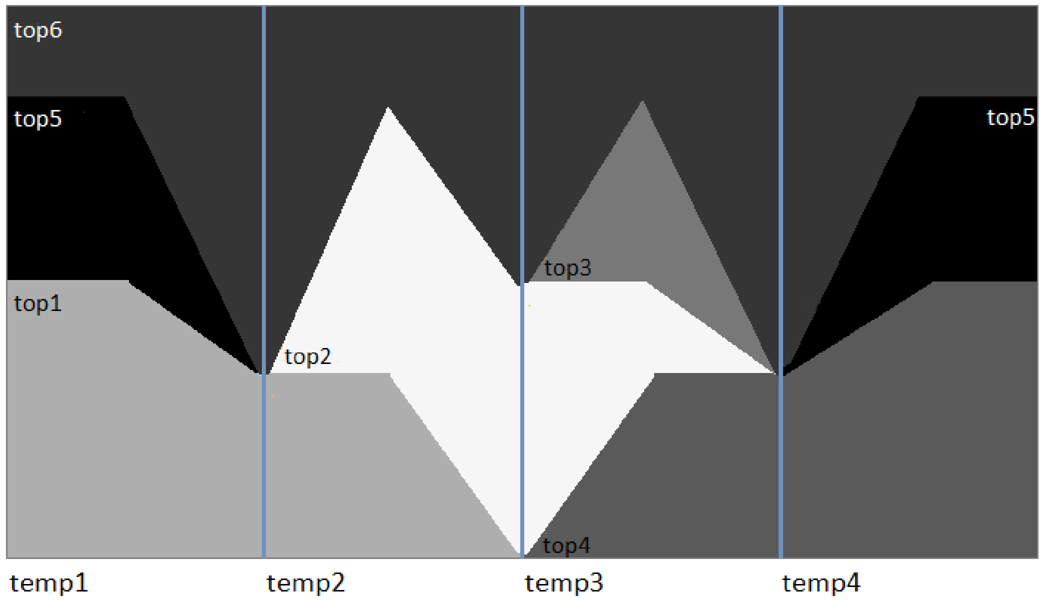

Figure 3: k=6 topical and h=4 temporal clusters generate 13 topical-temporal clusters.

with respect to the base monolithic profiles are displayed in Table 2.

Method	ndcg@10	prec@10	recall@nr
MONP	0.67622	0.65146	0.45806
RAND4	0.69035	0.66465	0.47869
TEMPS	0.70907	0.68139	0.49444
$\text{TOPS}_{sqrt(n/2)}$	0.73911	0.71351	0.52740
$\text{TOPS}_{mn/t}$	0.73721	0.71313	0.53491
$\text{TOPTEMPS}_{sqrt(n/2)}$	0.75416	0.72456	0.53072
$\text{TOPTEMPS}_{mn/t}$	**0.76136**	**0.73283**	**0.54520**

Table 1: Results of the experiments (best results in bold).

Method	% ndcg@10	% prec@10	% recall@nr
RAND4	2.09	2.02	4.50
TEMPS	4.86	4.59	7.94
$\text{TOPS}_{sqrt(n/2)}$	9.30	9.52	15.14
$\text{TOPS}_{mn/t}$	9.02	9.47	16.78
$\text{TOPTEMPS}_{sqrt(n/2)}$	11.53	11.22	15.86
$\text{TOPTEMPS}_{mn/t}$	**12.59**	**12.49**	**19.02**

Table 2: Percentages of improvement with respect to monolithic profiles.

First, we can observe that the behavior of the different systems with respect to the three metrics is essentially the same (the rankings of the systems for the three metrics are almost identical). For that reason we are going to focus on the ndcg@10 metric which, from the perspective of expert finding is probably the most relevant.

It can be seen that using subprofiles of any type is better than using the monolithic profiles. The differences are always statistically significant, using a paired t-test with the results of the five training-test partitions of the document collection, with significance level of 0.01.

Although the results obtained by the temporal subprofiles are better than those of the monolithic profiles, as the percentages of improvement are rather small (although significant), we want to test whether this improvement is really due to the temporal influence or merely to the fact that we are using several (four in this case) smaller subprofiles instead of a single big profile. In order to do so we have also randomly divided the interventions of each MP in the training set into four parts and generated a subprofile for each part. We have repeated this process 10 times and averaged the results obtained from these random subprofiles. The results are also shown in Tables 1 and 2, under the name RAND4.

We can observe that the (averaged) results of the random partitions are also better than monolithic profiles (and they are statistically significant too), although they are worse than the temporal subprofiles. The fact that random partitions are somewhat better than monolithic profiles is probably due to the smaller size of these subprofiles. This suggest that a part of the improvement obtained by TEMPS over MONP is not due to temporal influence but to the use of smaller subprofiles. Therefore, we can conclude that the contribution of temporal subprofiles alone to improve the recommendation results is positive but rather scarce.

On the other hand, the gains obtained by the topical subprofiles are more important (around 9%), and the differences with temporal

In these tables only the averages of the ten random partitions appear. The individual values are all quite similar, having very low standard deviations, on the order of 0.001.

The differences between random and temporal subprofiles are small but also statistically significant.

The IRS may tend to favor smaller documents.

subprofiles are also statistically significant. However, there is not significant differences between the two versions of TOPS using different number of topics. This is interesting because it suggests a robust behavior of TOPS.

The best results are obtained when combining the two types of subprofiles (with gains around 12% with respect to MONP). The results are significantly better than those obtained by topical subprofiles alone. Again, there are not significant differences between the two versions of topical-temporal subprofiles.

8 CONCLUDING REMARKS

In this paper we have studied the effects of using subprofiles temporally and/or topically homogeneous, in comparison with single heterogeneous profiles, for the problem of expert recommendation. The experiments have been carried out in a context of political expert finding, using a document collection of parliamentary documents.

The obtained results show that the use of homogeneous subprofiles instead of monolithic profiles is always positive to improve the recommendation quality, although the improvement degree varies depending on the different methods: temporal subprofiles are only a bit better than random subprofiles (of the same size), whereas topical subprofiles get much better results. So it seems that the topical dimension is more important than the temporal dimension. Nevertheless, there is a sinergy between both dimensions, as their combination produces the best results.

For future work we are planning to explore other ways of combining temporal and topical dimensions to get better subprofiles, as for example using temporal topic models [6, 27].

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REFERENCES

[1] M.Z. Al-Taie, S. Kadry, A.I. Obasa, Understanding expert finding systems: domains and techniques, Social Network Analysis and Mining 8:57, 2018.
[2] B. Amini, R. Ibrahim, M.S. Othman, A. Selamat, Capturing scholar's knowledge from heterogeneous resources for profiling in recommender systems, Expert Systems with Applications 41:7945-7957, 2014.
[3] C. Au Yeung, N. Gibbins, N. Shadbolt, Multiple interests of users in collaborative tagging systems, In King, I. and Baeza-Yates, R., editors, Weaving Services and People on the World Wide Web, pp. 255-274, Springer, 2009.
[4] K. Balog, Y. Fang, M. de Rijke, P. Serdyukov, L. Si, Expertise retrieval, Foundations and Trends in Information Retrieval 6:127-256, 2012.
[5] D.M. Blei, A.Y. Ng, M.I. Jordan, Latent Dirichlet allocation, Journal of Machine Learning Research 3:993-1022, 2003.
[6] D.M. Blei, J.D. Lafferty, Dynamic topic models, Proceedings of the 23rd international conference on Machine learning, pp. 113-120, 2006.
[7] J. Bobadilla, F. Ortega, A. Hernando, A. Gutiérrez, Recommender systems survey, Knowledge-Based Systems 46:109-132, 2013.
[8] C. Bouras, V. Tsogkas, Improving news articles recommendations via user clustering, International Journal of Machine Learning and Cybernetics 8:223-237, 2017
[9] P.G. Campos, F. Díez, I. Cantador, Time-aware recommender systems: A comprehensive survey and analysis of existing evaluation protocols, User Modeling and User-Adapted Interaction 24:67-119, 2014.
[10] F. Can, E. Ozkarahan, Concepts and effectiveness of the cover-coefficient-based clustering methodology for text databases. ACM Trans. Database Syst. 15(4):483-517, 1990.
[11] L. Chen, K. Sycara, Webmate: A personal agent for browsing and searching, In Proceedings of the Second International Conference on Autonomous Agents, pp. 132-139, 1998.
[12] L.M. de Campos, J.M. Fernández-Luna, J.F. Huete, Profile-based recommendation: A case study in a parliamentary context, Journal of Information Science 43(5):665-682, 2017.
[13] L.M. de Campos, J.M. Fernández-Luna, J.F. Huete, Committee-based profiles for politician finding, International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems 25(Suppl. 2):21-36, 2017.
[14] L.M. de Campos, J.M. Fernández-Luna, J.F. Huete, L. Redondo-Expósito, Automatic construction of multi-faceted user profiles using text clustering and its application to expert recommendation and filtering problems, Knowledge-Based Systems 190, article number 105337, 2020.
[15] Y. Ding, X. Li, Time weight collaborative filtering, In Proceedings of the 14th ACM International Conference on Information and Knowledge Management, pp. 485-492, 2005.
[16] C.I. Eke, A.A. Norman, L. Shuib, H.F. Nweke, A survey of user profiling: state-of-the-art, challenges, and solutions, IEEE Access 7:144907-144924, 2019.
[17] S. Gauch, M. Speretta, A. Chandramouli, A. Micarelli, User profiles for personalized information access. In: The Adaptive Web, Lecture Notes in Computer Science 4321:54-89 2007.
[18] J.A. Gulla, A.D. Fidjestøl, X. Su, H. Castejon, Implicit user profiling in news recommender systems, In Proceedings of the 10th International Conference on Web Information Systems and Technologies - Volume 1: WEBIST, pp. 185-192, 2014.
[19] L. Kaufman, P.J. Rousseeuw, Finding groups in data: An introduction to cluster analysis, John Wiley, 1990.
[20] Y. Koren, Collaborative filtering with temporal dynamics, Communications of the ACM 53:89-97, 2010.
[21] S. Lin, W. Hong, D. Wang, T. Li, A survey on expert finding techniques, Journal of Intelligent Information Systems 49:255-279, 2017.
[22] N. Nikzad-Khasmakhi, M.A. Balafar, M.R. Feizi-Derakhshi, The state-of-the-art in expert recommendation systems, Engineering Applications of Artificial Intelligence 82:126-147, 2019.
[23] C. Ramos Casimiro, I. Paraboni, Temporal aspects of content recommendation on a microblog corpus. In: Baptista J., Mamede N., Candeias S., Paraboni I., Pardo T.A.S., Volpe Nunes M..G. (eds) Computational Processing of the Portuguese Language. PROPOR 2014. Lecture Notes in Computer Science 8775:189-194, 2014.
[24] J. Rybak, K. Balog, K. Nørvåg, Temporal expertise profiling, In de Rijke, M., Kenter, T., de Vries, A. P., Zhai, C., de Jong, F., Radinsky, K., and Hofmann, K., editors, Proceedings of the 36th European Conference on IR Research, pp. 540-546, 2014.
[25] A. Sieg, B. Mobasher, R. Burke, Web search personalization with ontological user profiles. Proceedings of the 16th ACM International Conference on Information and Knowledge Management, pp. 525-534, 2007.
[26] G.L. Somlo, A.E. Howe, Incremental clustering for profile maintenance in information gathering web agents, In Proceedings of the Fifth International Conference on Autonomous Agents, pp. 262-269, 2001.
[27] X. Wang, A. McCallum, Topics over time: a non-Markov continuous-time model of topical trends, Proceedings of the 12th ACM SIGKDD international conference on Knowledge discovery and data mining, pp. 424-433, 2006.
[28] R. Yeniterzi, J. Callan, Moving from static to dynamic modeling of expertise for question routing in CQA sites, Proceedings of the Ninth International AAAI Conference on Web and Social Media, pp. 702-705, 2015.
[29] S. Yuan, Y. Zhang, J. Tang, W. Hall, J.B. Cabota, Expert finding in community question answering: a review, Artificial Intelligence Review, 2019 https://doi.org/10.1007/s10462-018-09680-6.