UNIVERSITY OF AMSTERDAM

UvA-DARE (Digital Academic Repository)

Finding Knowledgeable Groups in Enterprise Corpora

Liang, S.; de Rijke, M.

DOI
10.1145/2484028.2484109
Publication date
2013
Document Version
Final published version
Published in
SIGIR '13

Link to publication

Citation for published version (APA):
Liang, S., & de Rijke, M. (2013). Finding Knowledgeable Groups in Enterprise Corpora. In *SIGIR '13: the proceedings of the 36th International ACM SIGIR Conference on Research & Development in Information Retrieval : July 28-August 1, 2013, Dublin, Ireland* (pp. 1005-1008). ACM. https://doi.org/10.1145/2484028.2484109

General rights
It is not permitted to download or to forward/distribute the text or part of it without the consent of the author(s) and/or copyright holder(s), other than for strictly personal, individual use, unless the work is under an open content license (like Creative Commons).

Disclaimer/Complaints regulations
If you believe that digital publication of certain material infringes any of your rights or (privacy) interests, please let the Library know, stating your reasons. In case of a legitimate complaint, the Library will make the material inaccessible and/or remove it from the website. Please Ask the Library: https://uba.uva.nl/en/contact, or a letter to: Library of the University of Amsterdam, Secretariat, P.O. Box 19185, 1000 GD Amsterdam, The Netherlands. You will be contacted as soon as possible.

UvA-DARE is a service provided by the library of the University of Amsterdam (https://dare.uva.nl)

Download date:08 Oct 2026

Finding Knowledgeable Groups in Enterprise Corpora

Shangsong Liang
s.liang@uva.nl

Maarten de Rijke
derijke@uva.nl

ISLA, University of Amsterdam, Amsterdam, The Netherlands

ABSTRACT

The task of finding groups is a natural extension of search tasks aimed at retrieving individual entities. We introduce a group finding task: given a query topic, find knowledgeable groups that have expertise on that topic. We present four general strategies to this task. The models are formalized using generative language models. Two of the models aggregate expertise scores of the experts in the same group for the task, one locates documents associated with experts in the group and then determines how closely the documents are associated with the topic, whilst the remaining model directly estimates the degree to which a group is a knowledgeable group for a given topic. We construct a test collections based on the TREC 2005 and 2006 Enterprise collections. We find significant differences between different ways of estimating the association between a topic and a group. Experiments show that our knowledgeable group finding models achieve high absolute scores.

Categories and Subject Descriptors

H.3.1 [**Information Storage and Retrieval**]: Content Analysis and Indexing

Keywords

Group finding, expertise retrieval, language modeling

1. INTRODUCTION

A major challenge within any organization is managing the expertise within the organization such that groups with expertise in a particular area can be identified [2]. Rather than finding knowledgeable individuals, sometimes locating a *group* with appropriate skills and knowledge in an organization is of great importance to the success of a project being undertaken [6].

Traditional approaches to finding knowledge, whether in individuals or in groups within an organization, often include two main steps. For a given task the expertise of the experts in each group is recorded and then the expertise of a group is computed by aggregating the expertise values of all group members. Both steps are traditionally done manually and require considerable effort. In addition, this approach is usually restricted to a fixed set of expertise areas [7]. To reduce the effort of recording and evaluating the expertise of people from their representations, many automatic approaches have been proposed. There has been an increasing move to automatically extract such representations for evaluating expertise from heterogeneous document collections [2]. To compute the expertise values of a group, in principle, many aggregation operators are available, e.g., sum or average. These can be employed to combine individual experts' expertise values. There are at least 90 families of aggregation operators [11], which have been put to use in a range of applications. But the problem of how to aggregate expertise values of experts within a group so that the expertise scores of different groups can be easily compared and ranked is unknown.

We treat the problem of finding a knowledgeable group differently. Four distinct models are proposed. Our models are based on probabilistic language modeling techniques. Each model ranks groups according to the probability of the group being a knowledgeable group for a query topic, but the models differ in how this is performed. Three types of variable play a key role in our estimations: groups (G), queries (Q) and documents (D). The order in which we estimate these is reflected in our naming conventions. E.g., the model named GDQ proceeds by first collecting evidence of whether a group is knowledgeable on the topic via the experts in the group (G), and then determining whether each expert in the group has expertise on the topic via documents (D), and finally whether a document is talking about the given query (Q) topic.

2. RELATED WORK

Significant research effort has been invested in locating a group of individuals in an organization. Yang et al. [10] try to find a group of attendees familiar with a given activity initiator, and ensure each attendee in the group to have tight social relations with most of the members in the group. Sozio and Gionis [9] study a query-dependent variant of the community-detection problem: given a graph, and a set of nodes in the graph as their input query, find a subgraph that contains the input query nodes and is densely connected. Lappas et al. [6] study the problem of given a task, a pool of individuals χ with different skills and a social network that captures the compatibility among them, finding a subset of χ, who together have the skills to complete a task with minimal communication costs. Kargar and An [5] design communication cost functions for two types of communication structures.

The problem we deal with is different. We introduce a new group finding task: given a topic query, determine a list of knowledgeable groups within which the experts have expertise on the topic. Our group finding problem includes two sub-problems. The first is to answer questions such as "Which groups are knowledgeable groups on topic T?" whilst the second is to answer the question "What does group G know?" We focus on the first sub-problem.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.
SIGIR'13, July 28–August 1, 2013, Dublin, Ireland.
Copyright is held by the owner/author(s). Publication rights licensed to ACM.
Copyright 2013 ACM 978-1-4503-2034-4/13/07 ...$15.00.

3. MODELING GROUP FINDING

In our modeling of the knowledgeable group finding task, groups, documents and queries are considered in different orders. Groups are ranked according to how likely they have expertise on the given query according to the estimated language model.

Problem definition and context. We address the following problem: what is the probability of a group g being a knowledgeable group given query topic q? We have to estimate the probability of a group g given a query q and then rank groups according to this probability. The top k groups will be considered to be the most knowledgeable groups for the given query topic. Instead of computing this probability directly, we apply Bayes' Theorem, and obtain $p(g|q) = p(q|g)p(g)p(q)^{-1}$, where $p(q)$ is the probability of a query and $p(g)$ the probability of a group, both of which can be assumed to be uniform for a query and a group, considering that q is the same during retrieval and there is no group that is more likely to be relevant. Hence, ranking groups according $p(g|q)$ boils down to ranking a query topic given a group: $p(q|g)$. To determine $p(g|q)$ or $p(q|g)$ we consider experts, groups, documents and queries in different orders, so as to arrive at four distinct models.

Four group finding models. The first of four models for group finding is presented in some detail; because of lack of space, the others are presented much more concisely. We start with two types of aggregation model: the Group-Query-Document (GQD) model and the Group-Document-Query (GDQ) model. The order of the key terms in these names signifies the following: GQD means that the evidence of whether a group is knowledgeable on the topic is collected via the experts in the group (G), then how likely each expert in the group has expertise on each subtopics in the query (Q) topic is computed via the documents (D). GDQ denotes that the evidence of whether a group is knowledgeable is collected via the experts in the group (G), then via each document (D) the expertise of each expert in the group on the query (Q) topic is computed directly via the documents. We assume that experts in the same group g are conditionally independent given the group, such that:

$$p(g|q) = \prod_{ex \in g} p(ex|q)^{as(ex,g)},$$

where ex is an expert belonging to group g, $p(ex|g)$ is the probability of how likely an expert ex belonging to a group g, and $as(ex, g)$ is the association between an expert ex and the group g. Instead of computing $p(ex|g)$ directly, we apply Bayes' Theorem, and obtain $p(ex|q) = p(q|ex)p(ex)p(q)^{-1}$, where $p(q|ex)$ is the probability of a query given an expert, $p(ex)$ is the probability of an expert, and $p(q)$ is the probability of the query. As we assume that each expert is equally important, $p(ex)$ is assumed to be constant. Additionally, for each query topic, $p(q)$ is the same, hence, $p(ex|q)$ is proportional to $p(q|ex)$. So, $p(g|q)$ becomes

$$p(g|q) \stackrel{rank}{=} \prod_{ex \in g} p(q|ex)^{as(ex,g)}.$$

The GQD Model. To obtain $p(q|ex)$, we assume that each term t in query q is conditionally independent given expert ex, such that:

$$p(q|ex) = \prod_{t \in q} p(t|ex)^{n(t,q)},$$

where $p(t|ex)$ is the probability of a term given an expert and $n(t, q)$ is the number of occurrences of term t in query q. Combined, we can rewrite $p(g|q)$ as follows.

$$p(g|q) \stackrel{rank}{=} \prod_{ex \in g} \left\{ \prod_{t \in q} p(t|ex)^{n(t,q)} \right\}^{as(ex,g)}.$$

To obtain $p(t|ex)$, we take the sum over documents d in the collection. This can be expressed as $p(t|ex) = \sum_d p(t|d)p(d|ex)$, where $p(t|d)$ is the probability of term t given document d, and $p(d|ex)$ is the probability of d given expert ex. Now we can obtain the probability of a group given a query, i.e., our GQD model:

$$p(g|q) \stackrel{rank}{=} \prod_{ex \in g} \left\{ \prod_{t \in q} \left\{ \sum_d p(t|d)p(d|ex) \right\}^{n(t,q)} \right\}^{as(ex,g)}$$

The GDQ Model. We can compute the probability of a query q given an expert ex in a different way. By taking the sum over all documents d, $p(q|ex)$ can be obtained. Formally, this can be expressed as: $p(q|ex) = \sum_d p(q|d)p(d|ex)$, where $p(q|d)$ and $p(d|ex)$ are the probability of query q given document d and of document d given query q, respectively. Based on this, we obtain our second aggregation model, i.e., our GDQ model:

$$p(g|q) \stackrel{rank}{=} \prod_{ex \in g} \left\{ \sum_d \left\{ \prod_{t \in q} p(t|d)^{n(t,q)} \right\} p(d|ex) \right\}^{as(ex,g)}.$$

The DGQ model. Next we consider a *document* model. Instead of aggregating expertise scores of all the experts within a group as in our aggregation models, as the key terms DGQ in this model's name suggests, the probability $g(g|q)$ can be computed directly via the documents (D). For each we compute how likely the group (G) is associated with it, and how likely it is talking about the given query (Q) topic, such that: $p(g|q) = \sum_d p(g|d)p(d|q)$, where $p(g|d)$ and $p(d|q)$ are the probability of group g given document d and the probability of d given query q, respectively. This, then, is how $p(g|q)$ can be represented, i.e., our DGQ model:

$$p(g|q) \stackrel{rank}{=} \sum_d \left\{ \prod_{ex \in g} p(d|ex)^{as(ex,g)} \right\} \left\{ \prod_{t \in q} p(t|d)^{n(t,q)} \right\}.$$

The QDG model. Finally, we present a *query* model for group finding. We use "query model" not in the sense of building rich representations of a query but to indicate that our estimations of a group finding model start with the query. As the name QDG indicates, it first considers how likely a group knows about a query (Q) topic. QDG computes this via documents (D) and then determines how likely each expert in the group (G) is associated with each document. We collect evidence of how knowledgeable group g is via all documents in the collection and obtain $p(t|g) = \sum_d p(t|d)p(d|g)$, where $p(d|g)$ is the probability of document d given group g. The final version of $p(g|q)$ can then be represented as:

$$p(g|q) \stackrel{rank}{=} \prod_{t \in q} \left\{ \sum_d p(t|d) \prod_{ex \in g} p(d|ex)^{as(ex,g)} \right\}^{n(t,q)}.$$

And this is our QDG model. It first computes the probability of how likely a group is talking about a query topic; it collects evidence of how knowledgeable the group is for a given query via all documents in the collection. For each expert within a group, we determine how likely the expert is associated with the documents.

4. ASSOCIATIONS AND SMOOTHING

Expert-document associations. For all models described in the previous section, we need to be able to estimate the probability of an expert ex in group g being associated with document d. In recent years, this problem has attracted considerable attention [2]. Following Balog et al. [1], to define this probability, we assume that associations $a(d, ex)$ between experts ex and documents d have been calculated and define

$$p(d|ex) = \frac{a(d, ex)}{\sum_{d' \in D} a(d', ex)}, \quad (1)$$

where D is the set of documents in the collection, and $a(d, ex)$ is simply defined as to be 1 if if the full name or email address of expert ex (exactly) appears in document d, otherwise $a(d, ex) = 0$.

Group-expert associations. For all of the group finding models described in the previous section, we also need to be able to estimate the strength of the association between expert ex and group g to which the expert belongs. We define the following group expert association $as(ex, g) = |g|^{-1}$, where $|g|$ is the total number of experts within the group to which they belong.

Smoothing strategies. In our four models, the term $p(g|q)$ may contain zero probabilities due to data sparsity. E.g., in our aggregation models, GQD and GDQ, $p(g|q)$ will contain zero probabilities if there exist experts who have no expertise on the given query. Hence, we have to infer a group model θ_g, such that the probability of a group given a query model is $p(\theta_g|q)$. We employ Jelinek-Mercer smoothing [4] to estimate $p(\theta_g|q)$; we consider two types.

To facilitate comparisons and for the sake of uniformity, instead of estimating $p(g|q)$ directly, we can easily infer a document model θ_d such that the probability of term t given a document d model is $p(t|\theta_d)$, and infer an expert model θ_{ex} such that the probability of a document d given an expert ex is $p(d|\theta_{ex})$. The document model, then, is a linear interpolation of the background model $p(t)$ and the smoothed estimate: $p(t|\theta_d) = (1-\alpha)p(t|d) + \alpha p(t)$, where α is a smoothing parameter ($0 < \alpha < 1$). The expert model is a linear interpolation of the background model $p(d)$ and the smoothed estimate: $p(d|\theta_{ex}) = (1-\beta)p(d|ex)+\beta p(d)$, where β is a smoothing parameter ($0 < \beta < 1$). Let $\theta(\alpha, t, d)$ be short for $p(t|\theta_d) = (1-\alpha)p(t|d) + \alpha p(t)$, and $\vartheta(\beta, d, ex)$ be short for $p(d|\theta_{ex}) = (1-\beta)p(d|ex) + \beta p(d)$. Then, the group finding model GQD can be smoothed and estimated as

$$p(g|q) \overset{rank}{=} \prod_{ex \in g} \Big\{ \prod_{t \in q} \big\{ \sum_d \theta(\alpha, t, d) \cdot \vartheta(\beta, d, ex) \big\}^{n(t,q)} \Big\}^{as'},$$

where as' abbreviates $as(ex, g)$. The other group finding models, GDQ, DGQ, and QDG, can be smoothed and estimated in an analogous manner. As to the GDQ model:

$$p(g|q) \overset{rank}{=} \prod_{ex \in g} \Big\{ \sum_d \Big\{ \prod_{t \in q} \theta(\alpha, t, d)^{n(t,q)} \Big\} \vartheta(\beta, d, ex) \Big\}^{as'},$$

with as' as before. For the DGQ model we have

$$p(g|q) \overset{rank}{=} \sum_d \Big\{ \prod_{ex \in g} \vartheta(\beta, d, ex)^{as(ex,g)} \prod_{t \in q} \theta(\alpha, t, d)^{n(t,q)} \Big\},$$

and the QDG model can be smoothed and estimated as

$$p(g|q) \overset{rank}{=} \prod_{t \in q} \Big\{ \sum_d \theta(\alpha, t, d) \prod_{ex \in g} \vartheta(\beta, d, ex)^{as(ex,g)} \Big\}^{n(t,q)}.$$

For the GQD model, we also consider a second type of smoothing strategy with one parameter: $p(g|q) \overset{rank}{=} \prod_{ex \in g} \{ \prod_{t \in q} \{ (1-\lambda) \sum_d p(t|d)p(d|ex) + \lambda p(t) \}^{n(t,q)} \}^{as'}$.

5. EXPERIMENTAL SETUP

Next, we describe the experimental setup for testing our knowledgeable group finding methods. We specify our research questions, describe our data set, and detail our ground truth.

Research questions. We consider the following questions. How do different group finding models perform compared against each other, under different ground truths or different evaluation metrics? Are some queries harder than others for the same model? Finally: Are the models different from each other?

Experimental collection. For evaluation purposes we use data made available for the expert finding task at the TREC 2005 and 2006 Enterprise tracks [3, 8]. The document collection used is a crawl of the World Wide Web Consortium (W3C; 330K documents, 5.7GB). The expert finding qrels for the two years differ: in 2005, 50 working group titles were the test topics for the expert finding task, resulting in 1509 expert-group pairs, with 2 to 391 experts in the same group and approximately 30 experts per group on average; names and e-mail addresses of 1092 expert candidates (W3C members) are given as part of the collection. For the TREC 2006 expert finding task, 55 queries queries were created, but only 49 are provided with expert finding ground truth.

Three types of ground truth. We use the qrels of the TREC 2006 expert finding task and propose three types of ground truth: *binary*, *graded* and *number*.

Binary A working group g is considered relevant for topic q if there is at least one expert ex who is a member of g (according to the TREC 2005 expert finding qrels) and has expertise on the topic q (according to the TREC 2006 expert finding qrels).

Grade A slightly more sophisticated definition of group relevance uses grades: the level of relevance of group g for query q is defined based on the fraction of the experts in the group. We distinguish between $|L|$ different levels of relevance, i.e., {0, 1, 2, ..., $|L-1|$}. The relevance grade of group g for topic q is defined as follows: let $f(g, q) = \frac{|\{ex \in g : rel(ex,q)=1\}|}{|g|}$, where $\{ex \in g : rel(ex, q) = 1\}$ is the set of experts in g with expertise on topic q according to the TREC 2006 expert finding qrels and $|g|$ is the total number of experts in group g. If $\frac{1}{|L|} \cdot l \leq f(g, q) < \frac{1}{|L|} \cdot (l+1)$, the grade level for this group is l. In this paper, we set $|L| = 10$.

Number Here, the level of relevance of group g for query q is defined based on the number of experts in the group. For instance, if there are 15 experts who have expertise on the given query topic, then the level of the relevance for this group is 15. The level of relevance ranges from 0 to 30 with a majority smaller than 4.

Runs. We run our experiments with all documents in the collection for our four group finding models. We perform a grid search to find optimal settings of the smoothing parameters (with 0.1 increments). We generate runs on the full collection and on subsets defined by taking the top n documents returned by a standard document retrieval run when using the topic as query. Evaluation measures used are MAP, precision@5, 10, nDCG and nDCG@5, 10 against our three types of ground truth. Evaluation was done using the trec_eval program (available from `http://trec.nist.gov`).

6. RESULTS

We start by comparing the results of the optimized models with two smoothing parameters. Next, we present the results of query differences. Finally, we test whether the models smoothed by two or one parameters are statistically significantly different.

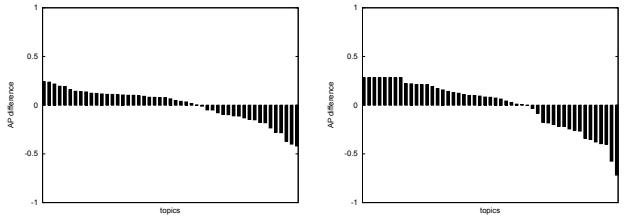
Model comparison. How do our knowledgeable group finding models perform compared to each other? For each specific performance evaluation metric, we compare the models using optimal smoothing parameters. We use two parameters α and β to smooth the proposed four knowledgeable group finding models, i.e., GQD, GDQ, DGQ and QDG.

Table 1 lists the scores for the various metrics. Clearly, DGQ outperforms the other models on all metrics using the binary and graded ground truth, but GDQ outperforms DGQ on all metrics using the number ground truth. QDG model is the worst performing model for all metrics and against all types of ground truth. The table also shows that GQD, GDQ and DGQ have a similar performance for all metrics against all types of ground truth. (The MAP and p@N scores against the number ground truth are the same as those against the binary ground truth, and are therefore omitted.)

Query differences. Our aim here is to find out whether some queries are harder than others for the same model against the metrics. We turn to a topic-level analysis of the MAP performance for

Table 1: Evaluation results for all optimal models with two smoothing parameters, using the binary, graded and number ground truths. For each metric, we report the evaluation results, followed by the optimal smoothing parameters α and β.

Ground			NDCG@									p@					
truth	Model	NDCG	α	β	5	α	β	10	α	β	MAP	α	β	5	α	β	10	α	β
binary	GQD	.8861	.1	.2	.8165	.1	.2	.7850	.1	.3	.7127	.1	.7	.8041	.1	.9	.7306	.1	.3
	GDQ	.9009	.1	.9	.8291	.3	.5	.7936	.2	.5	.7552	.1	.9	.8122	.1	.6	.7408	.2	.8
	DGQ	**.9133**	.1	.9	**.8680**	.1	.9	**.8420**	.1	.9	**.7772**	.1	.9	**.8571**	.1	.9	**.7918**	.1	.9
	QDG	.7623	.1	.2	.5604	.1	.1	.5568	.1	.2	.4882	.1	.4	.5592	.1	.1	.5265	.1	.2
graded	GQD	.8245	.2	.3	.7237	.2	.3	.7595	.1	.2	.7403	.1	.3	.6367	.1	.1	.5224	.1	.2
	GDQ	.8457	.1	.4	.7675	.2	.3	.7945	.1	.4	.7673	.1	.4	.6776	.1	.3	.5510	.1	.4
	DGQ	**.8631**	.2	.9	**.7991**	.5	.9	**.8160**	.7	.8	**.8092**	.6	.8	**.7102**	.5	.6	**.5531**	.7	.9
	QDG	.3916	.1	.8	.1012	.1	.1	.1282	.1	.2	.2182	.1	.4	.1714	.1	.1	.1673	.1	.1
number	GQD	.7964	.1	.9	.6210	.1	.8	.6730	.6	.8									
	GDQ	**.8160**	.1	.9	**.6496**	.1	.9	**.6905**	.1	.9									
	DGQ	.7907	.1	.9	.6062	.1	.9	.6758	.1	.9									
	QDG	.6222	.1	.2	.3328	.1	.1	.4258	.1	.1									



(a) GQD, binary (b) GQD, graded

Figure 1: Topic-level differences from the mean scores for GQD using the binary/number and graded ground truths.

each model against binary/number, graded ground truth. We plot the differences in performances (per topic) between the average AP score and the AP score per topic, sorted by performance difference. Fig. 1(a) shows the plots for GQD when using the binary/number ground truth, whilst Fig. 1(b), shows the plots for GQD when using the graded ground truth. From Fig. 1(a), it is clear that the performance in MAP does not differ dramatically from the mean when using the binary or number ground truths. In comparison, for some topics the performance is dramatically worse than the mean for GQD when using the graded ground truth. (We observed similar phenomena for the other three models.)

Statistical significance. Finally, we determine whether the observed differences between our group finding approaches with two smoothing parameters strategy are statistically significant. We use a two-tailed paired t-test between two models on NDCG and MAP data and test for significance differences at the 0.95 confidence level. Table 2 indicates that when using NDCG as a metric the differences between GQD and GDQ against graded ground truth are not significant. This is also true for the differences between GQD and DGQ, and between GDQ and DGQ against the graded and number ground truth. When using MAP, the differences between all models are statistically significant except for those between GQD and GDQ. We also test differences between the optimal GQD model with smoothing with two parameters and with a single smoothing parameter based on NDCG and MAP against three types of ground truth; there are no statistically significant differences at the 0.95 confidence level except based on NDCG against binary ground truth where the p value is 0.0270. Hence, we cannot really distingush between GQD with smoothing with two parameters and GQD with smoothing with one parameter in our experiments.

Table 2: Two-tailed paired t-test between different models on NDCG and MAP metrics.

metric	ground truth	GQD vs. GDQ	GQD vs. DGQ	GQD vs. QDG	GDQ vs. DGQ	GDQ vs. QDG	DGQ vs. QDG
NDCG	binary	.0107	.0005	.0000	.0496	.0000	.0000
	graded	**.2349**	**.0616**	.0000	**.2282**	.0000	.0000
	number	.0086	**.4107**	.0000	**.0570**	.0000	.0000
MAP	bin./numb.	.0013	.0000	.0000	.0198	.0000	.0000
	graded	**.2647**	.0140	.0000	.0221	.0000	.0000

7. CONCLUSIONS

We have introduced a group finding task. We proposed four models, GQD, GDQ, DGQ and QDG. We also constructed an experimental collection by using the TREC 2005 and 2006 Enterprise collections. We introduced three kinds of ground truth and evaluated our models along many dimensions. Directly collecting expertise evidence from documents is the most effective way to find knowledgeable groups when using the binary or graded ground truths, and aggregating the expertise of each experts in the same group can also be a good way to find the groups. Our models are not very sensitive to changes of the parameters when using a two parameter smoothing strategy. We found statistically significant differences between the models when using MAP scores based on multiple types of ground truth.

Acknowledgements. We thank our reviewers for their helpful comments. This research was supported by the European Community's Seventh Framework Programme (FP7/2007-2013) under agreements 258191 (PROMISE) and 288024 (LiMoSINe), the Netherlands Organisation for Scientific Research (NWO) under nrs 640.004.802, 727.011.005, 612.001.116, HOR-11-10, the Center for Creation, Content and Technology (CCCT), the BILAND project funded by the CLARIN-nl program, the Dutch national program COMMIT, the ESF Research Network Program ELIAS, the Elite Network Shifts project funded by the Royal Dutch Academy of Sciences (KNAW), and the Netherlands eScience Center under number 027.-012.105.

8. REFERENCES

[1] K. Balog, L. Azzopardi, and M. de Rijke. Formal models for expert finding in enterprise corpora. In *SIGIR'06*, 2006.
[2] K. Balog, Y. Fang, M. de Rijke, P. Serdyukov, and L. Si. Expertise retrieval. *Foundations and Trends in Information Retrieval*, 6(2-3): 127–256, 2012.
[3] N. Craswell, A. P. de Vries, and I. Soboroff. Overview of the TREC 2005 enterprise track. In *TREC'05*, 2005.
[4] F. Jelinek and R. Mercer. Interpolated estimation of markov sourceparameters from sparse data. In *Proceedings of the Workshop on Pattern Recognition in Practice*, 1980.
[5] M. Kargar and A. An. Discovering top-k teams of experts with/without a leader in social networks. In *CIKM'11*, 2011.
[6] T. Lappas, K. Liu, and E. Terzi. Finding a team of experts in social networks. In *KDD'09*, pages 467–475, 2009.
[7] G. A. Pryor, J. W. Myles, D. R. R. Williams, and J. K. Anand. Team management of the elderly patient with hip fracture. *The Lancet*, pages 401–403, 1988.
[8] I. Soboroff, A. P. de Vries, and N. Craswell. Overview of the TREC 2006 enterprise track. In *TREC'06*, 2006.
[9] M. Sozio and A. Gionis. The community-search problem and how to plan a successful cocktail party. In *KDD'10*, pages 939–948, 2010.
[10] D.-N. Yang, Y.-L. Chen, W.-C. Lee, and M.-S. Chen. On social-temporal group query with acquaintance constraint. In *VLDB'11*, 2011.
[11] S.-M. Zhou, F. Chiclana, R. I. John, and J. M. Garibaldi. Alpha-level aggregation. *IEEE Trans. Knowl. and Data Eng.*, 23:1455–1468, 2011.