Adapting Voting Techniques for Online Forum Thread Retrieval

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Abstract. Online forums or message boards are rich knowledge-based communities. In these communities, thread retrieval is an essential tool facilitating information access. However, the issue on thread search is how to combine evidence from text units(messages) to estimate thread relevance. In this paper, we first rank a list of messages, then we score threads by aggregating their ranked messages’ scores. To aggregate the message scores, we adopt several voting techniques that have been applied in ranking aggregates tasks such as blog distillation and expert finding. The experimental result shows that many voting techniques should be preferred over a baseline that treats a thread as a concatenation of its message texts.

Keywords: Forum thread search, Ranking aggregates, Voting techniques

1 Introduction

Online forums are virtual places(communities) that facilitate seeking and sharing knowledge through in depth discussions. A user starts a discussion through posting an initial message, then other users read the initial message and answer it through reply messages. The initial message and its replies form a threaded discussion(thread). One challenge in accessing information in forums is information overload. Thread retrieval is one way to tackle it. However, the actual contents are not the threads but the messages. Therefore, given a query, a retrieval system must infer the thread relevance using the message text. In that aspect, thread retrieval resembles ranking aggregates tasks such as blog feed retrieval[14,16] and expert finding[7]. In these tasks, given a query, the objective is to rank aggregates (blogs, experts) by leveraging associated text units (blogs’ postings, experts’ writings)[8]. An analogy between ranking aggregates and thread retrieval is that threads are the aggregates, and messages are the associated texts or documents.

Voting techniques performed well in ranking aggregates tasks[7,6,8]. However, the effectiveness of each voting technique varies between tasks and datasets[8]. In addition to that, threads have a conversational structure that does not exist in other ranking aggregates contexts. In threads, the meaning of a message is fully understood within its discussion context. Furthermore, messages are mostly
replies, hence they tend to be shorter than blogs’ postings and experts’ writings. In other words, that might alter the performance of voting techniques. In this paper, we review several voting methods and investigate their performance on thread retrieval.

2 Voting in Thread Retrieval

Voting techniques were first proposed by [7] to the expert finding task. In voting techniques, we first rank a list of documents (e.g., expert’s writings) based on their relevance to the given query. Then, we rank aggregates (e.g., the experts) based on their scores obtained from fusing their ranked documents’ scores or ranks. Similarly, in this work, given a query $Q = \{q_1, q_2, ..., q_n\}$, we first rank a list of messages $R_Q$ with respect to $Q$. Then, we score threads by aggregating their ranked messages’ scores or ranks. In addition, threads are ranked based on their obtained aggregated scores in a descending order.

In estimating the relevance between the query $Q$ and a message $M$, we employ the query language model [12] assuming term independence, uniform probability distribution for $M$ and Dirichlet smoothing as follows [17]:

$$P(Q|M) = \prod_{q \in Q} \left( \frac{n(q, M) + \mu P(q|C)}{|M| + \mu} \right)^{n(q, Q)}$$  \hspace{1cm} (1)

where $q$ is a query term, $\mu$ is the smoothing parameter. $n(q, M)$ and $n(q, Q)$ are the term frequencies of $q$ in $M$ and $Q$ respectively, $|M|$ is the number of tokens in $M$, and $P(q|C)$ is the collection language model. The outputs of $P(Q|M)$ and $P(Q|C)$ are probabilistic values.

To rank threads, the twelve aggregation methods proposed by [7] are adapted: Votes, Reciprocal Rank(RR), BordaFuse, CombMIN, CombMAX, CombMED, CombSUM, CombANZ, CombMNZ, expCombSUM, expCombANZ and exp-CombMNZ. In addition to these methods, this study uses CombGNZ—the geometric mean of the relevance scores. We use this method because it is the aggregation method employed by [5,13].

In these methods, the relevance between a thread $T$ and $Q$, $rel(T, Q)$, is the score obtained through the aggregation of all $T$’s ranked messages $R_T$ as shown below:

$$rel_{\text{Votes}}(Q, T) = |R_T|$$  \hspace{1cm} (2)

$$rel_{\text{RR}}(Q, T) = \sum_{M \in R_T} \frac{1}{rank(Q, M)}$$  \hspace{1cm} (3)

$$rel_{\text{BordaFuse}}(Q, T) = \sum_{M \in R_T} |R_Q| - rank(Q, M)$$  \hspace{1cm} (4)

$$rel_{\text{CombMIN}}(Q, T) = \min_{M \in R_T} P(Q|M)$$  \hspace{1cm} (5)

$$rel_{\text{CombMAX}}(Q, T) = \max_{M \in R_T} P(Q|M)$$  \hspace{1cm} (6)
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\[ rel_{\text{CombMED}}(Q,T) = \text{Median}_{M \in R_T} P(Q|M) \]  
(7)

\[ rel_{\text{CombSUM}}(Q,T) = \sum_{M \in R_T} P(Q|M) \]  
(8)

\[ rel_{\text{CombANZ}}(Q,T) = \frac{1}{|R_T|} \times \sum_{M \in R_T} P(Q|M) \]  
(9)

\[ rel_{\text{CombGNZ}}(Q,T) = \left( \prod_{M \in R_T} P(Q|M) \right)^{\frac{1}{|R_T|}} \]  
(10)

\[ rel_{\text{CombMNZ}}(Q,T) = |R_T| \times \sum_{M \in R_T} \exp(P(Q|M)) \]  
(11)

\[ rel_{\text{expCombSUM}}(Q,T) = \sum_{M \in R_T} \exp(P(Q|M)) \]  
(12)

\[ rel_{\text{expCombANZ}}(Q,T) = \frac{1}{|R_T|} \times \sum_{M \in R_T} \exp(P(Q|M)) \]  
(13)

\[ rel_{\text{expCombMNZ}}(Q,T) = |R_T| \times \sum_{M \in R_T} \exp(P(Q|M)) \]  
(14)

where \( \text{rank}(Q,M) \) is the rank of the message \( M \) in \( R_Q \), \( |R_Q| \) is the size of \( R_Q \), and \( |R_T| \) is the number of \( T \)'s ranked messages.

As an illustrative example, let \( R_Q = \{M_1, M_2, M_3, M_4, M_5, M_6\} \) denote a list of ranked messages, where there are 3 threads associated with these messages \( T_1, T_2 \) and \( T_3 \); and, \( M_1 \) belongs to \( T_1 \), \( M_2 \) and \( M_3 \) belong to \( T_2 \) and \( M_4, M_5 \) and \( M_6 \) belong to \( T_3 \). In addition, let the relevance scores between the user query and these messages assigned by query language relevance model to be 0.06, 0.05, 0.04, 0.03, 0.02 and 0.01 respectively, whereas the ranks of these messages are 1, 2, 3, 4, 5, 6. Then, we calculate the relevance between the given query \( Q \) and the thread \( T_6 \) using the Votes, the CombSUM and the BordaFuse aggregation methods as follows: \( rel_{\text{Votes}}(Q,T_6) = |R_{T_6}| = 3 \), \( rel_{\text{CombSUM}}(Q,T_6) = P(Q|M_4) + P(Q|M_5) + P(Q|M_6) = 0.04 + 0.05 + 0.06 = 0.16 \), \( rel_{\text{BordaFuse}}(Q,T_6) = 6 - \text{rank}(Q,M_4) + 6 - \text{rank}(Q,M_5) + 6 - \text{rank}(Q,M_6) = 6 + 1 + 0 = 16 \).

3 Related Studies

The voting techniques approach to the ranking aggregates tasks are inspired by works on data fusion (meta search)\[15,11,1\]. A meta search algorithm aims to combine several ranked lists of documents into a unified list\[1\]. These ranked lists are generated by various retrieval methods. The essences of the data fusion are two folds\[16\]. First, the more retrieval methods retrieve a particular document, the more the document is expected to be relevant to the user query. Second, a document that is ranked at top ranking positions by many retrieval methods
might be more relevant than a one that was found at the bottom of several ranked lists. Data fusion can be categorized into score based and rank based aggregation methods. The score based methods — such as [15]'s CombMAX, CombMIN, CombMED and CombSUM methods, use the relevance scores of documents, whereas the rank based methods, [1], utilize the ranking positions of these documents on the ranked lists.

[7,6] approached the problem of ranking aggregates as a data fusion problem: each document is an evidence about its parent aggregate’s relevance to the query. Generally, the voting approach was found to be statistically superior to baseline methods [7,6]. However, the performance of each voting technique was not consistent across tasks [8]: the CombMAX method, which performed well on the expert finding setting, was significantly worse than the baseline methods on the blog distillation setting [6]. Therefore, how will these methods perform on the thread retrieval task is the focus of this study.

Several combination techniques have been proposed to address evidence combination for thread retrieval. [5] proposed two strategies to rank threads: inclusive and selective. The inclusive strategy utilizes evidence from all messages in order to rank parent threads. Two models from previous work on blog site retrieval [4] were adapted to thread search: the large document and the small document models. The large document model creates a virtual document for each thread by concatenating the thread’s message texts, then it scores threads based on their virtual document relevance to the query. In contrast, the small document model defines a thread as a collection of text units (messages). Then, it scores threads by adding up their messages relevance scores. In contrast to the inclusive strategy, [5]’s selective strategy treats threads as collections of messages; and it uses only few messages to rank threads. Three selective methods were used. The first one is scoring threads using only the initial message relevance score. The second method scores threads by taking the maximum score of their message relevance scores. The third method is based on the Pseudo Cluster Selection (PCS) method [14]. PCS scores threads in two steps: it scores a list of messages, then it ranks threads by taking the geometric mean of the top $k$ ranked messages’ scores from each thread. Generally, it was found that the selective models are statistically superior to the inclusive models [5,3]. Our work extends this selective strategy by investigating more aggregation methods.

Another line of research is the multiple context retrieval approach proposed by [13]. This approach treats a thread as a collection of several local contexts—types of self-contained text units. Four contexts were proposed: posts — identical to messages, pairs, dialogues and the entire thread. The thread and post contexts are identical to [5]’s virtual document and message based representations. In the pair and the dialogue contexts, the conversational relationship between messages is exploited to build text units. In the pair context, for each pair of messages $m_i, m_j$ that have a reply relationship — $m_j$ is a reply to $m_i$, a text unit
is built by concatenating their texts. In the dialogue context, for each chain of replies that starts from the initial message; and, there is a reply relation between each message and its neighbor in the chain, a text unit is built by concatenating the chain’s message texts. To rank threads using the post, pair and dialogue contexts, PCS was used. It was observed that the retrieval using the dialogue context outperformed retrieval using other contexts. Additionally, the weighted product between the thread context and the dialogue contexts achieved the best performance. In our work, we are focusing on how to combine the ranked contexts’ relevance scores. Therefore, our work is complementary to [13]’s work.

The third line of work is the structure based document retrieval proposed by [2]. In this approach, a thread consists of a collection of structural components: the title, the initial message and the reply messages set. In this representation, the thread relevance to the user query is estimated using [10]’s inference network framework. Our work can be applied to [2]’s representation as well. We could use [2]’s inference based relevance score the same way the thread context score was used in [13].

4 Experimental Design

Thread retrieval is a new task, and the number of test collections is limited. In this study, we used the same corpus used by [2]. It has two datasets from two forums—Ubuntu[1] and Travel[2] forums. The statistics of the corpus is given in Table 1. Text was stemmed with the Porter stemmer, and stopword removal was applied at the ranking stage. In conducting the experiments, we used the Indri retrieval system[3].

|                               | Ubuntu | Travel |
|-------------------------------|--------|--------|
| No of threads                 | 113277 | 83072  |
| No of users                   | 103280 | 39454  |
| No of messages                | 676777 | 590021 |
| No of queries                 | 25     | 25     |
| No of judged threads          | 4512   | 4478   |

As for evaluation, we use [5]’s virtual document model $VD$ as a baseline. This model has been used as a strong baseline in previous studies [5,13,2]. For each query, we calculated the standard used measures on Ad Hoc retrieval [9]: Precision at 10 (P@10), Normalized Discounted Cumulative Gain at 10 (NDCG@10),

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1. [ubuntuforums.org](http://ubuntuforums.org)
2. [http://www.tripadvisor.com/ShowForum-g28953-i4-New York.html](http://www.tripadvisor.com/ShowForum-g28953-i4-New York.html)
3. [http://www.lemurproject.org/indri.php](http://www.lemurproject.org/indri.php)
Mean Reciprocal Rank (MRR) and Mean Average Precision (MAP). In all experiments, we used the same relevance protocol followed in [2,13], a thread is considered as relevant if its relevance level is greater or equal to 1— if it is partially or highly relevant; and, it is irrelevant if the relevance level is zero.

As for parameter estimation, we estimated the smoothing parameters, $\mu$, for the virtual document and message language models. In addition, for all voting techniques, we estimated the size of the initial ranked list of messages $R_Q$. To estimate $\mu$, we varied its value from 500 up to 4000; adding 500 in each run. To estimate the size of $R_Q$, we varied its value from 500 up to 5000 adding 500 in each run. Then, an exhaustive grid search was applied to maximize MAP using 5-fold cross validation.

5 Result and Discussion

Table 2. Retrieval performance of the voting methods on the Ubuntu dataset

| Method       | MAP   | MRR   | P@10 | NDCG@10 |
|--------------|-------|-------|------|---------|
| VD           | 0.3437 | 0.7258 | 0.4200 | 0.3284 |
| CombGNZ      | 0.2727 $\Delta$  | 0.4974 ▼  | 0.2760 ▽  | 0.1971 ▽  |
| Votes        | 0.2749 ▽  | 0.6550 ▽  | 0.4680 ▽  | 0.3551 ▽  |
| RR           | 0.3313 ▽  | 0.6287 ▽  | 0.4600 ▽  | 0.3428 ▽  |
| BordaFuse    | 0.3153 ▽  | 0.6913 ▽  | 0.5080 ▽  | 0.3778 ▽  |
| CombMIN      | 0.1779 ▽  | 0.5000 ▽  | 0.2600 ▽  | 0.1849 ▽  |
| CombMAX      | 0.3074 ▽  | 0.6420 ▽  | 0.4480 ▽  | 0.3257 ▽  |
| CombMED      | 0.2212 ▽  | 0.5021 ▽  | 0.2760 ▽  | 0.1927 ▽  |
| CombSUM      | 0.3100 ▽  | 0.6667 ▽  | 0.4720 ▽  | 0.3633 ▽  |
| CombANZ      | 0.2314 ▽  | 0.4971 ▽  | 0.2800 ▽  | 0.1991 ▽  |
| CombMNZ      | 0.3108 ▽  | 0.6933 ▽  | 0.4880 ▽  | 0.3720 ▽  |
| expCombSUM   | 0.3088 ▽  | 0.6933 ▽  | 0.4840 ▽  | 0.3676 ▽  |
| expCombANZ   | 0.2315 ▽  | 0.4971 ▽  | 0.2800 ▽  | 0.1991 ▽  |
| expCombMNZ   | 0.3088 ▽  | 0.6933 ▽  | 0.4840 ▽  | 0.3676 ▽  |

The symbols $\Delta$ and ▲ denote statistically significant improvements over the virtual document model (VD) at p-value < 0.01 and 0.05 respectively using paired randomization test. Similarly, ▽ and ▼ denote statistically significant degradations over (VD) at p-value < 0.01 and 0.05 respectively.

Table 2 and Table 3 present the retrieval performance of the voting methods on thread retrieval for the Ubuntu dataset and the Travel dataset respectively. Several observations can be found from the data shown in these tables. The first observation is the performance of the aggregation methods as compared to the baseline method—the virtual document (VD) model. In high precision measures (P@10 and NDCG@10), RR, BordaFuse, CombSUM, CombMNZ, expCombSUM, expCombANZ, and expCombMNZ are able to produce better or
Table 3. Retrieval performance of the voting methods on the Travel dataset

| Method     | MAP   | MRR   | P@10  | NDCG@10 |
|------------|-------|-------|-------|---------|
| VD         | 0.3774| 0.6967| 0.4800| 0.3549  |
| CombGNZ    | 0.2001| 0.4838| 0.3320| 0.2319  |
| Votes      | 0.3066| 0.7491| 0.5080| 0.4063  |
| RR         | 0.3155| 0.6120| 0.4520| 0.3431  |
| BordaFuse  | 0.3630| 0.7547| 0.5640| 0.4350  |
| CombMIN    | 0.1574| 0.4843| 0.3040| 0.2199  |
| CombMAX    | 0.2724| 0.5754| 0.4360| 0.3216  |
| CombMED    | 0.2004| 0.4841| 0.3480| 0.2388  |
| CombSUM    | 0.3668| 0.8000| 0.5560| 0.4440  |
| CombANZ    | 0.2065| 0.4841| 0.3400| 0.2346  |
| CombMNZ    | 0.3575| 0.7790| 0.5280| 0.4205  |
| expCombSUM | 0.3513| 0.7937| 0.5200| 0.4109  |
| expCombANZ | 0.2065| 0.4841| 0.3400| 0.2346  |
| expCombMNZ | 0.3513| 0.7937| 0.5200| 0.4109  |

The symbols △ and ▲ denote statistically significant improvements over the virtual document model (VD) at p-value < 0.01 and 0.05 respectively using paired randomization test. Similarly, ▽ and ▼ denote statistically significant degradations over (VD) at p-value < 0.01 and 0.05 respectively.

comparable result with respect to VD. These methods favour threads with highly ranked messages. In contrast, CombGNZ, CombMED, CombANZ, CombMIN and expCombANZ might be effected by threads that have a lot of low scored messages. This behaviour was also reported in applying voting techniques to expert finding[6]. Therefore, based on [7]’s conclusion, we assert that highly ranked messages are good indicators of relevant threads.

To confirm this conclusion, the effects of varying the size of the initial ranked list was studied. As Figure 1 and Figure 2 show, the retrieval performance decreases as the size gets relatively big (more than 1000). In addition, one can see that almost all methods suffer from this problem except RR and CombMAX. This is expected because RR and CombMAX address the problem of low scored messages inherently. RR adds up the inverse of the messages’ ranks, thus it penalizes threads with a lot of low ranked messages. In the case of CombMAX, it takes only the best scoring message; therefore, if no threads are introduced as the size increases, the order of threads will not change. That explains the convergence of CombMAX and RR and the consistent decrement of the other methods. This was replicated with other measures such as P@10 and NDCG@10 (Not shown in this paper) as well. This indicates the importance of highly ranked messages to thread retrieval.

Another observation is the importance of utilizing non score signals. For instance, the Votes method’s performance is relatively good as compare to other methods. Similarly, CombMNZ, which makes use of the number of ranked messages in addition to sum of scores, has similar performance as well. All of these
methods leverage information that is not coming from scores: the number of ranked messages. Nevertheless, exhaustive emphasis on these signals will hurt the performance. One could see that from fast decrement of Votes and CombMNZ methods as size increases. One possible reason is that adding up low scores has
less impact than multiplying by the number of these messages; CombSUM’s decrement is always less than those of the Votes and the CombMNZ methods. Although the voting methods improvements are not statistically significant, they are consistent on both datasets and require only using the message index. That gives the voting approach an extra advantage over the virtual document model because it coincides with what users contribute, hence it frees the retrieval system from re-concatenating messages into a virtual document whenever a new message is created or edited.

6 Conclusion

In this paper, we studied applying voting techniques to online forums thread retrieval. We used thirteen voting methods that aggregate ranked messages scores or ranks in order to score the parent threads. The experimental result shows that voting techniques—RR, BordaFuse, CombSUM, CombMNZ, expCombSUM, expCombSUM and expCombMNZ, that favour threads with highly ranked messages produced comparable or better performance as compare to baselines; and, none of them is a winning method. Although the observed improvements were not statistically significant, we recommend using the voting methods because their improvements are consistent across datasets, and they coincide with what users contribute.

Nevertheless, this paper finding has motivated us to further study the effects of voting techniques when aggregating only the top $k$ messages. Another future direction is incorporating these voting methods into [13]'s multiple context models. Similar approach will be applied to incorporate the structural component representation of [2].

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References

1. J. A. Aslam and M. Montague. Models for metasearch. In Proceedings of the 24th annual international ACM SIGIR conference on Research and development in information retrieval, SIGIR '01, pages 276–284, New York, NY, USA, 2001. ACM.
2. S. Bhatia and P. Mitra. Adopting inference networks for online thread retrieval. In Proceedings of the Twenty-Fourth AAAI Conference on Artificial Intelligence, pages 1300–1305, Atlanta, Georgia, USA., July 11–15 2010.
3. J. L. Elsas. Ancestry.com online forum test collection. Technical Report CMULTI-017, Language Technologies Institute, School of Computer Science, Carnegie Mellon University, 2011.
4. J. L. Elsas, J. Arguello, J. Callan, and J. G. Carbonell. Retrieval and feedback models for blog feed search. In Proceedings of the 31st annual international ACM SIGIR conference on Research and development in information retrieval, SIGIR ’08, pages 347–354, New York, NY, USA, 2008. ACM.
5. J. L. Elsas and J. G. Carbonell. It pays to be picky: an evaluation of thread retrieval in online forums. In Proceedings of the 32nd international ACM SIGIR conference on Research and development in information retrieval, SIGIR ’09, pages 714–715, New York, NY, USA, 2009. ACM.
6. C. Macdonald and I. Ounis. Key blog distillation: ranking aggregates. In Proceedings of the 17th ACM conference on Information and knowledge management, CIKM ’08, pages 1043–1052, New York, NY, USA, 2008. ACM.
7. C. Macdonald and I. Ounis. Voting techniques for expert search. Knowl. Inf. Syst., 16(3):259–280, Aug. 2008.
8. C. Macdonald and I. Ounis. Learning models for ranking aggregates. In Proceedings of the 33rd European conference on Advances in information retrieval, ECIR’11, pages 517–529, Berlin, Heidelberg, 2011. Springer-Verlag.
9. S. Mark. Test collection based evaluation of information retrieval systems. Foundations and Trends in Information Retrieval, 4:247375, 2010.
10. D. Metzler and W. B. Croft. Combining the language model and inference network approaches to retrieval. Inf. Process. Manage., 40(5):735–750, Sept. 2004.
11. P. Ogilvie and J. Callan. Combining document representations for known-item search. In Proceedings of the 26th annual international ACM SIGIR conference on Research and development in information retrieval, SIGIR ’03, pages 143–150, New York, NY, USA, 2003. ACM.
12. J. M. Ponte and W. B. Croft. A language modeling approach to information retrieval. In Proceedings of the 21st annual international ACM SIGIR conference on Research and development in information retrieval, SIGIR ’98, pages 275–281, New York, NY, USA, 1998. ACM.
13. J. Seo, W. Bruce Croft, and D. Smith. Online community search using conversational structures. Information Retrieval, 14:547–571, 2011. 10.1007/s10791-011-9166-8.
14. J. Seo and W. B. Croft. Blog site search using resource selection. In Proceedings of the 17th ACM conference on Information and knowledge management, CIKM ’08, pages 1053–1062, New York, NY, USA, 2008. ACM.
15. J. A. Shaw, E. A. Fox, J. A. Shaw, and E. A. Fox. Combination of multiple searches. In The Second Text REtrieval Conference (TREC-2), pages 243–252, 1994.
16. A. Spoerri. Authority and ranking effects in data fusion. J. Am. Soc. Inf. Sci. Technol., 59(3):450–460, Feb. 2008.
17. C. Zhai and J. Lafferty. A study of smoothing methods for language models applied to information retrieval. ACM Trans. Inf. Syst., 22(2):179–214, Apr. 2004.