RELEVANCE FEEDBACK AS AN INDICATOR TO SELECT THE BEST SEARCH ENGINE

Evaluation on TREC Data

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Abstract: This paper explores information retrieval system variability and takes advantage of the fact two systems can retrieve different documents for a given query. More precisely, our approach is based on data fusion (fusion of system results) by taking into account local performances of each system. Our method considers the relevance of the very first documents retrieved by different systems and from this information selects the system that will perform the retrieval for the user. We found that this principle improves the performances of about 9%. Evaluation is based on different years of TREC evaluation program (TREC 3, 5, 6 and 7), TREC-adhoc tracks. It considers the two and five best systems that participate to TREC the corresponding year.

1 INTRODUCTION

Evaluation programs have pointed out a high variability on information retrieval system (IRS) results. (Harman, 1994; Buckley & Harman, 2004) shows for example that system performance is topic-dependant and that two different systems can perform differently for a same topic or information need.

Table 1 illustrates this through local and global performances of two different IRS that participated to the 7th session of the. TREC (Text REtrieval Conference) evaluation program. The results of both systems (runs) respectively labelled *CLARIT98COMB* and *T7miti1* are displayed. The performances are estimated according to usual evaluation measures used in evaluation frameworks such as TREC. These measures are the Mean Average Precision (MAP) computed as the mean of average precisions over a set of queries, and the precision at n (P@n) computed as the precision after n retrieved documents (n takes usually the values 5, 10, 15, 20, 30, 100, 200, 500, and 1000).

Local performance corresponds to the one obtained for two given TREC 7 ad-hoc topics (Table 1a) whereas global performance corresponds to the one when averaged over a set of 50 topics (Table 1b). Table 1a) shows that if it was possible to automatically predict that the run *CLARIT98COMB* is better than the run *T7miti1* for topic 352 and *T7miti1* better than *CLARIT98COMB* for topic 354, then MAP could be improved when averaged over the topics. Furthermore, there are numerous topics where *CLARIT98COMB* and *T7miti1* have alternately the best MAP. This adds interest to automatically predict the system leading to the best results for a given topic.

In this paper, the hypothesis we make is that prediction can be based on the relevance of the very first retrieved documents. As relevance feedback, the principle is to evaluate the first retrieved documents. However, in relevance feedback, relevant documents are used to select new terms to add to the initial query. In our approach, the relevant documents are used to order systems. The best system is then selected to treat the current query.

Table 1: Local and global performances for two systems from ad-hoc TREC 7.

a) Local performances for 2 topics and 2 systems from TREC 7 ad-hoc.

Topic	352	
Run	CLARIT98COMB	T7miti1
Retrieved documents	1000	210
Relevant documents	246	246
Relevant documents retrieved	216	117
Map	0.5068	0.3081
P@5	1.0000	0.6000
P@10	1.0000	0.7000
P@15	0.9333	0.6000
P@20	0.8000	0.6500
Topic	354	
Run	CLARIT98COMB	T7miti1
Retrieved documents	1000	486
Relevant documents	361	361
Relevant documents retrieved	124	190
Map	0.1675	0.2767
P@5	1.0000	0.4000
P@10	1.0000	0.3000
P@15	1.0000	0.3333
P@20	0.8500	0.4500

b) Global performances for 2 systems from TREC 7 ad-hoc.

	CLARIT98COMB	T7miti1
Map	0.3702	0.3675
P@5	0.6920	0.6640
P@10	0.6940	0.6400
P@15	0.6613	0.6213
P@20	0.6180	0.5780

2 RELATED WORKS

(Fox & Shaw, 1994) consider different sub-collections of TREC 2 and combine different search strategies in different ways. They show that fusing results of different searches improves performances compared to single searches. One of the best fusing technique is CombSUM which consists in adding the document-query similarity values.

(Lee, 1997) shows that CombSUM is particularly efficient when it is based on the level of overlapping sets of relevant and non-relevant document retrieved. He shows that fusing two systems that have a high degree of overlapping of relevant documents is more efficient than fusing two systems that have a high degree of overlapping of non–relevant documents.

The study presented in (Beitzel et al., 2003) leads to different conclusions. It shows that improvement is related to the number of relevant documents that occur in a single retrieved set rather than on the overlapping degree of the different sets.

Like in these approaches, the method we present in this paper considers different systems, but as opposed to the data fusion techniques that combine different system results, our approach rather select the system that will conduce the search. The selected system can differ from one query to the other. The best system is selected considering relevance-feedback principle.

3. FUSING METHOD AND EVALUATION FRAMEWORK

3.1. Fusing system results based on highly relevant documents

Our method is based on several systems that retrieve in parallel documents. The top documents retrieved by each system are analysed. Based on the relevance of these top documents, one system is selected to retrieve the documents for the user.

Algorithm 1: Selecting the best system

```
For each topic Tj
    For each system Si
        Search documents
        Consider the n first retrieved documents to
        the user for relevance evaluation
        Compute precision at n documents (P@n)
    End For
    Order systems per decreasing P@n
    Select the first system
    Retrieve documents to the user using this
    selected system
End For
```

3.2 TREC evaluation framework

Text REtrieval Conference provides benchmark collections. Ad-hoc track in TREC corresponds to the case when a user expresses his information need and expects the relevant documents to be retrieved. This track started at the first TREC session (TREC 1). For that reason, there are several ad-hoc collections available now.

A ad-hoc collection consists of a document set, a query set (50 topics) and the set of relevant documents for each of the queries (called qrels).

TREC participants send the documents their system retrieves for each query of the current session (or year). This is called a "run". Each run is then evaluated according to the qrels.

Table 2 provides details on the collections and systems that participate at the corresponding session.

Table 2: TREC collection features.

Session	TREC3	TREC5	TREC6	TREC7
Topics	151-200	251-300	301-350	351-400
# runs	48	48	74	103

System performance is evaluated considering to different criteria which are detailed in (Voorhees & Harman, 2001) and computed thanks to the trec_eval tool. Mean Average Precision (MAP) is one of the most used criteria to compare systems among them. P@5 is also a usual criterion. It is related to high precision and corresponds to the system precision when 5 documents are retrieved.

4 RESULTS

We applied the method we suggest first using the two best systems (the ones that get the best MAP in the corresponding TREC session) and then using the five best systems. Results are presented in table 3 and 4 and in sections 4.1 and 4.2 respectively.

4.1. Fusing the two best systems

In this section, we consider the two best systems (the ones that get the best MAP in the corresponding TREC session). For each topic, depending on the P@5 value, one or the other system is selected to retrieve documents to the user.

Table 3: Local and Global MAP when considering the two best systems

TREC3	Inq102 (1st)	Citya1	Optimal	Fusion
Local (first five queries)	0.6259 0.2699 0.1806 0.7372 0.2504	0.5783 0.5667 0.2681 0.7354 0.0035	0.6259 0.5667 0.2681 0.7372 0.2504	0.6259 0.5667 0.2681 0.7372 0.2504
Global	0.4226	0.4012	0.4647 (+9.96%)	0.4576 (+8.28%)
TREC5	**ETHme1 (1st)**	**Uwgcx1**	**Optimal**	**Fusion**
Local (first five queries)	0.0673 0.0453 0.6813 0.3262 0.1660	0.2215 0.0932 0.8600 0.2909 0.0543	0.2215 0.0932 0.8600 0.3262 0.1660	0.2215 0.0453 0.6813 0.3262 0.1660
Global	0.3165	0.3098	0.3900 (+23.22%)	0.3684 (+16.40%)
TREC6	**uwmt6a0 (1st)**	**CLAUG**	**Optimal**	**Fusion**
Local (first five queries)	0.3185 0.7671 0.6556 0.5000 0.0302	0.4753 0.5819 0.6779 0.2599 0.0600	0.4753 0.7671 0.6779 0.5000 0.0600	0.4753 0.7671 0.6556 0.2599 0.0600
Global	0.4631	0.3742	0.5079 (+9.67%)	0.4773 (+3.04%)
TREC7	**CLARIT98 COMB (1st)**	**T7miti**	**Optimal**	**Fusion**
Local (first five queries)	0.7112 0.5068 0.4281 0.1675 0.4555	0.8366 0.3081 0.3388 0.2767 0.5429	0.8366 0.5068 0.4281 0.2767 0.5429	0.7112 0.5068 0.3388 0.1675 0.5429
Global	0.3702	0.3675	0.4341 (+17.26%)	0.4069 (+9.91%)

Table 3 presents the results, where « Optimal » corresponds to the MAP if, for each query, we could have chosen the best system. Thus it corresponds to the maximum MAP any system could obtain when selecting the best system for each query among the systems. In this table, we detail the 5 first topics as well as average over the topic set. On the different rows, data in brackets corresponds to the variation in percentage when compared with the best system of the session. For example, regarding TREC 3 and the first query, *Inq102* gets the best MAP and is selected for that query when computing the "optimal" value. When averaged over the queries, this optimal technique would obtain MAP of 0.4647, which corresponds to an improvement of 9.96% compared to the best system that year (*Inq102* obtained 0.4226).

In table 3, « Fusion » indicates the MAP that is obtained automatically by our method. The system that is selected for a query is the one that obtained the best P@5. For example, regarding TREC 3 and the first query, *Inq102* obtained a better P@5 than *Citya1*; for that reason, it is selected to treat the first query. When averaged over the 50 queries, this fusion technique obtains MAP 0.4576, which corresponds to an improvement of 8.28% compared to *Inq102*, which was the best system that year in terms of MAP.

Whatever the collection (TREC session), when averaged over the 50 queries, MAP after fusion is better than the MAP obtained by the two systems separately. Regarding the automatic method, MAP is improved of more than 8% in most cases (+8.28% TREC 3; +16.40% TREC 5; +9.91% TREC 7). However, we can quote a variability of the improvement over the years. Indeed, improvement is lower when considering TREC 6 (+3.04%). One hypothesis for this lower improvement is related to the high initial performances of the best system that year (MAP of 0.4631). This hypothesis is supported by the results obtained using the other TREC collections. In TREC 5, the best system gets 0.3165 MAP and our fusion method leads to MAP 0.3684, which corresponds to an improvement of 16.40% compared to the best system that year. The best system in TREC 7 gets 0.3702 and our method obtained 0.4069 (+9.91%); in TREC 3 the best MAP is 0.4226 and we obtain 0.4576 (+8.28%). Finally the best MAP in TREC 6 is 0.4631 and our method gets 0.4773 (+3.04%). The first hypothesis is that the lower initial results, the higher improvements. An additional hypothesis could be that variability in results is lower when MAP is high. However, a further analysis performed in this direction has not fully supported this second hypothesis.

Table 3 shows that when considering the first 5 topics, generally, the automatic selection is relevant. For example in TREC 3 our selection method selects the right system for the 5 queries; in TREC 5 3 choices over 5 are correct.

Note that initial MAP the different systems get does not give indication on how the fusion will perform. For example, when considering TREC 5, the difference between the two best systems *ETHme1* and *Uwgcx1* is 0.0067. However, fusing their results is very effective (potentially, fusing these two systems can improve by more than 23% MAP and our method leads to improve the results more than 16%). On the opposite, regarding TREC 6 collection, the difference between the two best systems, *uwmt6a0* and *CLAUG*, is of 0.0889; however, fusing these two systems could lead to a 10% improvement and our method improves of about 3%. This could be explained by the distribution of topics according to the system that obtains the best result. Indeed, regarding TREC 5, the topics are divided nearly equitably when considering the two best systems *ETHme1* and *Uwgcx1*. *ETHme1* is the best for 52% of the topics and *Uwgcx1* is the best for 48% of the topics. On the opposite, regarding TREC 6 the topics are not divided equitably between the two best systems *uwmt6a0* and *CLAUG*. The system *uwmt6a0* is the best for 60% of the topics.

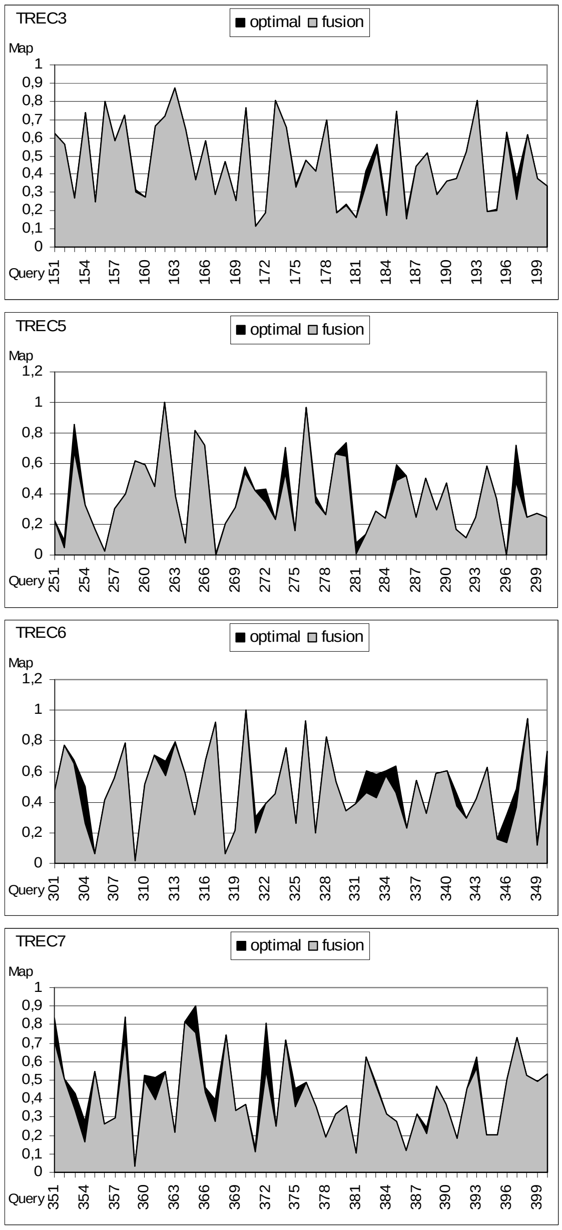


Figure 2: Local performances when fusing the 2 best systems with regard to the optimal possibility

Figure 2 illustrates the difference between the optimal fusing possibility and our method that fuses the two best systems. We show the results according to the different TREC collections. We can see that there are much more points for which the optimal curve and fusion curve differ for TREC 6 and TREC 7 than for TREC 3 and TREC 5. Indeed, results obtained with our fusing method are closer to the optimal possibility for TREC 3 (about 17% under the optimal value) and TREC 5 (about 30% under the optimal value) collections.

4.2. Fusing the five best systems

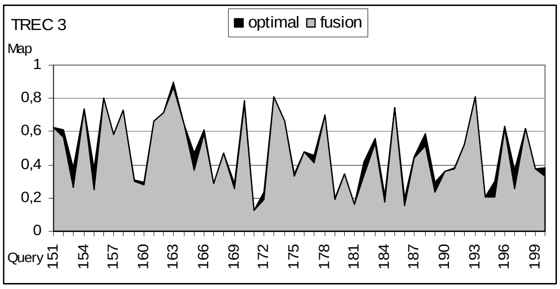
In this section, we study the effect of using more systems in our fusing method. We consider the five best systems with regard to MAP for each TREC session.

One first comment is that potentially, improvements can be much higher. For example regarding TREC 3, using two systems could lead at a maximum of about 0.46 for MAP, which corresponds to an improvement of about 10% compared to the best system. When using five systems, the maximum MAP could be of about 0.48, which corresponds to about 14% of improvement compared to the best system. The same type of difference between using two and five systems occurs in all the TREC sessions.

However, when applying our automatic method to select the best system, then the difference using two or five systems is smaller. For example, regarding TREC 3, our method obtained the same MAP when using two or five systems (0.4576 using two systems and 0.4593 using five). However, regarding TREC 5, MAP is of 0.3684 (+16.40% compared to the best system) using two systems but reaches 0.3786 (+19.62%) using five systems. It is important to notice that using more systems is more efficient when initial MAP are low (e.g. TREC 5).

Table 4: Global MAP considering the five best systems

Global MAP	Best run	Optimal	Fusion
TREC3	0.4226	0.4837 (+14.46%)	0.4593 (+8.68%)
TREC5	0.3165	0.4128 (+30.43%)	0.3786 (+19.62%)
TREC6	0.4631	0.5217 (+12.65%)	0.4703 (+1.55%)
TREC7	0.3702	0.4820 (+30.20%)	0.4067 (+9.86%)



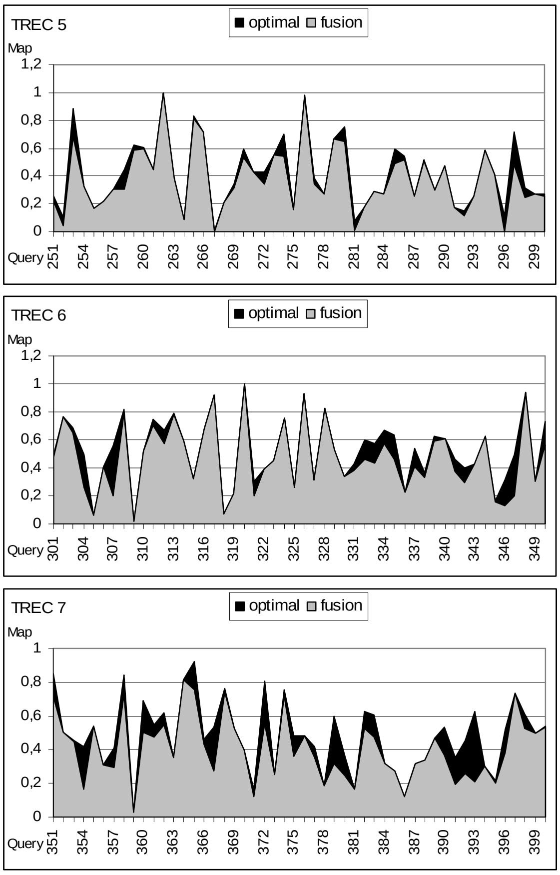


Figure 3: Local performances when fusing the 2 best systems with regard to the optimal possibility

Figure 3 illustrates the difference between the optimal fusing possibility and our method fusing the five best systems according to the different TREC collections. As for fusion of two systems (cf Figure 2), more differences can be observed between optimal curve and fusion curve for TREC 6 and TREC 7 than for TREC 3 and TREC 5. Indeed, results obtained with our fusing method are closer to the optimal possibility for TREC 3 (about 40% under the optimal value) and TREC 5 (about 35% under the optimal value) collections. Differences between fusing method and optimal possibility are stronger when fusing the five best systems than when fusing only the two best systems.

5 CONCLUSION

In this paper, we consider a new IR system fusing method. This method is based on system selection rather than on fusing system results. We first consider the perfect fusion in which the correct system is manually chosen in order to know what is the potential of the method. Even if we use the best systems in our method (ie. the systems that get the best MAP), we show that potentially MAP could be improved of about 15% (average results over the TREC sessions) when using two systems and about 22% when using five systems. This corresponds to the maximum of improvement we could get when selecting correctly the systems. Using our method based on P@5 we obtained on average 9.4% of improvement when using two systems and 9.9% when using five systems. These results lead to two main conclusions: the method we present is efficient however, there is room for more improvements, specifically using more systems.

In a further analysis, we have explored the hypothesis according to which variability in results is lower when MAP is higher. This hypothesis would support the fact that there is more potentiality to fuse the best systems using our method when the task is difficult. However this analysis has led to the conclusion that there is no direct correlation between the variability in each query considered individually and the possibility for our method to improve the results.

Future works will investigate different directions. First, our approach is based on precision at 5 (P@5); we would like to analyse the effect of the number of documents chosen in order to see if fewer documents would be enough. A second direction concerns evaluation. We would like to consider residual collection evaluation, that means that we would delete judged documents when evaluate the results. This will be crucial if we want to consider other performance measures such as high precision. Longer term studies concern first a way to predict the effectiveness of the method. We show that variability is not a good predictor of that but other direction have to be explored and probably combined such as the number of retrieved documents, the type of query, the models used in the search engines considered, etc.. Finally another future work is related to different fusion techniques. We would like to consider different query features in order to predict which system would be the best to select to treat the query. This could be combined with relevance information as studied in this paper. (He & Ounis, 2003) and (Mothe & Tanguy, 2005) open tracks in this direction considering query difficulty prediction as a clue to perform better information retrieval.

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REFERENCES

Harman, D., 1994. Overview of the Third Text REtrieval Conference (TREC-3), *3rd Text Retrieval Conference*, NIST Special Publication 500-226, pp 1-19.

Beitzel, S. M., Frieder, O., Jensen, E. C., Grossman, D. Chowdhury A., Goharian, N., 2003. Disproving the fusion hypothesis: an analysis of data fusion via effective information retrieval strategies. *SAC'03, ACM symposium on Applied computing*, pp. 823-827.

Buckley, C., Harman, D., 2004. The NRRC reliable information access (RIA) workshop. *27th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pp. 528-529.

Fox E. A., Shaw, J. A., 1994. Combination of Multiple Searches. *2nd Text Retrieval Conference (TREC-2)*, NIST Special Publication 500-215, pp. 243-252.

He, B., Ounis, I., 2003. University of Glasgow at the Robust Track – A query-based Model Selection Approach for Poorly-performing Queries. *12th Text Retrieval Conference (TREC-12)*, NIST Special Publication 500-255, pp. 636-645.

Lee, J., 1997. Analysis of multiple evidence combination. *22th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pp. 267-276.

Mothe, J., Tanguy, L., 2005. Linguistic features to predict query difficulty - A case study on previous TREC campaign. *SIGIR workshop on Predicting Query Difficulty - Methods and Applications*, pp. 7-10.

Voohrees E., Harman, D., 2001. Overview of TREC 2001. *10th Text Retrieval Conference*, NIST Special Publication 500-255, pp. 1-15.