

# Integrating Clusters Created Offline with Query-Specific Clusters for Document Retrieval

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## ABSTRACT

Previous work on cluster-based document retrieval has used *either* static document clusters that are created offline, or query-specific (dynamic) document clusters that are created from top-retrieved documents. We present the potential merit of integrating these two types of clusters.

**Categories and Subject Descriptors:** H.3.3 [Information Search and Retrieval]: Retrieval models

**General Terms:** Algorithms, Experimentation

**Keywords:** cluster-based retrieval, re-ranking

## 1. INTRODUCTION

Utilizing information induced from clusters of similar documents has long been suggested as a means to improving document-retrieval effectiveness [1].

Cluster-based document-retrieval models utilize mainly two types of clustering. The first is *static* (offline) clustering performed prior to retrieval time [1, 3, 4]. Information induced from static clusters is used to rank the corpus in response to a query. Since the clustering is query-independent, the clusters that presumably pertain to a given query have to be identified at retrieval time. A potential merit of using static clustering, for example, is that relevant documents that exhibit low surface-level query-similarity can still be identified if they are associated with (belong to) clusters with documents that exhibit high query-similarity. Thus, *vocabulary mismatch* between a query and relevant documents can be addressed.

*Dynamic* (query-specific) clusters are created from the documents most highly ranked by an initial search performed in response to a query [6, 4]. The clusters are often used to re-rank these initially highly-ranked documents so as to improve precision at the very top ranks [2]. In contrast to static clusters, dynamic clusters need to be computed for each query. Furthermore, they do not contain documents exhibiting very low surface-level query similarity. Nevertheless, dynamic clusters are more “query-focused” than static

clusters by the virtue of the way they are created, and hence, are somewhat less likely to exhibit *query drift* [5].

Static and dynamic clusters were used separately in work on cluster-based document retrieval. We demonstrate the potential merit of integrating the two types of clusters.

## 2. RETRIEVAL FRAMEWORK

Let  $q$ ,  $d$ , and  $\mathcal{D}$  denote a query, a document, and a corpus, respectively.

Dynamic clusters have been used for the re-ranking task [6, 4, 2]. That is, re-ordering the documents in an initial list,  $\mathcal{D}_{init}$ , that was retrieved in response to  $q$  by some search algorithm so as to improve precision at top ranks. Hence, we focus on this task, and present methods that rank only documents  $d$  in  $\mathcal{D}_{init}$ .

Our algorithms operate in the language modeling framework. We use  $p_x(y)$  to denote the language-model-based similarity between texts  $x$  and  $y$ .<sup>1</sup> (A text can be a query, a document, or a cluster of documents; we describe the estimate in Section 3.)

We assume that the corpus  $\mathcal{D}$  is clustered prior to retrieval time into *static* clusters. We use  $S$  to denote the set of  $m_s$  static clusters  $c$  that exhibit the highest query-similarity  $p_c(q)$ . Hence, while static clusters are created in a query-independent fashion, we use those that could be considered as “query-related”. In addition, we cluster  $\mathcal{D}_{init}$ , the list to be re-ranked, into the set  $T$  of  $m_t$  *dynamic* clusters.

The re-ranking methods that we present are based on the *interpolation* algorithm [3, 2]. The algorithm was shown to yield state-of-the-art performance when using static clusters to rank the entire corpus and when using dynamic clusters to re-rank  $\mathcal{D}_{init}$ . Specifically, if  $X$  is a set of clusters, the retrieval score of document  $d$  is:  $\lambda p_d(q) + (1 - \lambda) \sum_{c \in X} p_c(q) p_d(c)$ ;  $\lambda$  is a free parameter. Note that clusters serve as proxies for  $d$  for estimating query similarity.

**Re-ranking algorithms.** A previously-proposed re-ranking algorithm [2], **Interp(T)**, utilizes only query-specific clusters as proxies for  $d$ :  $\lambda p_d(q) + (1 - \lambda) \sum_{t \in T} p_t(q) p_d(t)$ . Another reference comparison that we consider is the **Interp(S)** method [3] that uses only static clusters as proxies for  $d$ :  $\lambda p_d(q) + (1 - \lambda) \sum_{s \in S} p_s(q) p_d(s)$ . Naturally, then, we can use both sets of clusters as proxies for  $d$  so as to leverage the merits of each (refer back to Section 1). The resul-

<sup>1</sup> $p_x(y)$  can be thought of as a surrogate for the probability  $p(y|x)$  often used in work on language models for information retrieval; refer to [3] for more details.

corpus	queries	disk(s)	ROBUST		AP		WSJ		SJMN	
			p@5	p@10	p@5	p@10	p@5	p@10	p@5	p@10
ROBUST	301-450,		48.2	43.2	44.6	43.5	55.6	49.8	33.2	28.7
	601-700	4,5 (-CR)	48.3	44.0 <sup>o</sup>	45.5	43.5	57.6	50.0	33.6	28.7
AP	51-150	1-3	50.2 <sup>t</sup>	45.1 <sup>t</sup>	50.1 <sup>t</sup>	47.8 <sup>to</sup>	60.8	53.4 <sup>t</sup>	36.0	32.9 <sup>to</sup>
WSJ	151-200	1-2	50.0	<b>45.7<sup>to</sup></b>	51.3 <sup>to</sup>	49.3 <sup>to</sup>	60.8	<b>57.0<sup>to</sup></b>	37.4 <sup>t</sup>	33.8 <sup>to</sup>
SJMN	51-150	3	49.3	45.1 <sup>t</sup>	49.3	48.2 <sup>to</sup>	60.8 <sup>t</sup>	54.6 <sup>to</sup>	37.4	33.7 <sup>to</sup>
			50.0	45.0 <sup>t</sup>	51.5 <sup>to</sup>	<b>49.8<sup>to</sup></b>	61.6	55.0 <sup>to</sup>	<b>39.0<sup>to</sup></b>	<b>35.0<sup>to</sup></b>
			<b>50.9<sup>to</sup></b>	45.2 <sup>t</sup>	<b>51.7<sup>to</sup></b>	49.6 <sup>to</sup>	<b>62.0<sup>t</sup></b>	55.4 <sup>to</sup>	38.4 <sup>t</sup>	34.6 <sup>to</sup>

**Table 1: Corpora used for experiments and performance numbers. The best result in a column is boldfaced. Statistically significant differences with the initial ranking (init. rank.) of  $\mathcal{D}_{init}$ , the optimized baseline (opt. base.), and  $\text{Interp}(T)$ , are marked with ‘i’, ‘o’, and ‘t’, respectively. (There are no statistically-significant differences between the performance of  $\text{Interp}(S)$  and that of the models that utilize both  $S$  and  $T$ .)**

tant algorithm,  $\text{Interp}(S \cup T)$ , scores  $d$  by:  $\lambda p_d(q) + (1 - \lambda) \sum_{c \in S \cup T} p_c(q) p_d(c)$ .

Another approach that we propose here is based on utilizing inter-cluster similarities. Specifically, we let one type of clusters serve as a proxy for the other type for estimating cluster-query and document-cluster similarities. For example, the  $\text{Interp}(T \rightarrow S)$  algorithm uses dynamic clusters as proxies for  $d$  and static clusters as proxies for dynamic clusters:  $\lambda p_d(q) + (1 - \lambda) \sum_{s \in S, t \in T} p_s(q) p_t(s) p_d(t)$ . Analogously,  $\text{Interp}(S \rightarrow T)$  uses static clusters as proxies for  $d$  and dynamic clusters as proxies for static clusters:  $\lambda p_d(q) + (1 - \lambda) \sum_{s \in S, t \in T} p_t(q) p_s(t) p_d(s)$ .

### 3. EVALUATION

The TREC corpora specified in Table 1 were used for experiments. We applied tokenization, Porter stemming, and stopword removal (using the INQUERY list) via the Lemur toolkit (www.lemurproject.org), which was also used for language-model induction. Topic titles served as queries.

We use a previously-proposed language-model-based similarity estimate, which was shown to be effective for cluster-based retrieval [3]. Specifically, let  $p_z^{Dir[\mu]}(\cdot)$  be the Dirichlet-smoothed unigram language model (with smoothing parameter  $\mu$ ) induced from text  $z$ . Then,  $p_x(y) \stackrel{def}{=} \exp\left(-D\left(p_y^{Dir[0]}(\cdot) \parallel p_x^{Dir[\mu]}(\cdot)\right)\right)$ , where  $D$  is the KL divergence. Unless otherwise specified, we set  $\mu = 1000$ .

Since the goal of re-ranking methods is to improve precision at top ranks, we use the precision of the top 5 and 10 documents (p@5, p@10) for evaluation measures. Statistically-significant differences of performance are determined using the Wilcoxon two-tailed test at a 95% confidence level.

Following previous work on re-ranking [2], we set the list  $\mathcal{D}_{init}$  upon which re-ranking is performed to the 50 documents  $d$  in the corpus that yield the highest  $p_d(q)$  (i.e., standard language-model-based retrieval), where  $\mu$  is set to optimize MAP; hence, the **initial ranking** of  $\mathcal{D}_{init}$  is of high quality. As a reference comparison we use an **optimized baseline** that ranks the corpus by  $p_d(q)$  with  $\mu$  set to optimize p@5. The value of  $\lambda$  is chosen for each re-ranking method from  $\{0, 0.1, \dots, 0.9\}$  to optimize p@5.

Each of the cluster-sets  $S$  and  $T$  is composed of  $m_s = m_t = 50$  nearest-neighbors-based clusters of 10 documents that are created using the  $p_x(y)$  similarity estimate [3, 2]. Studying the effect of the number of clusters, and the cluster size, on performance is left for future work. A cluster is represented by the concatenation of its constituent docu-

ments. The order of concatenation has no effect since we use unigram language models that assume term independence.

We can see in Table 1 that both the algorithms that use either static ( $S$ ) or dynamic ( $T$ ) clusters, and our newly-proposed algorithms that integrate the two, are highly effective in re-ranking. Indeed, the performance of the methods transcends that of the initial ranking and the optimized baseline — often to a statistically significant degree — in most relevant comparisons (corpus  $\times$  evaluation measure).

We can also see that our  $\text{Interp}(S \rightarrow T)$  and  $\text{Interp}(S \cup T)$  algorithms outperform  $\text{Interp}(T)$  and  $\text{Interp}(S)$  in most relevant comparisons. (However, the differences are rarely statistically significant.) Furthermore,  $\text{Interp}(S \cup T)$  is the only algorithm among those in Table 1 that posts statistically-significant improvements over the initial ranking for all relevant comparisons. These findings attest to the merits of utilizing *both* static and dynamic clusters.

Finally, we postulate that the performance of  $\text{Interp}(T \rightarrow S)$  is inferior to that of  $\text{Interp}(S \rightarrow T)$  and  $\text{Interp}(S \cup T)$  because  $\text{Interp}(T \rightarrow S)$  uses static *query-independent* clusters as proxies for dynamic query-specific clusters for estimating cluster-query similarities.

### 4. CONCLUSION AND FUTURE WORK

We demonstrated the potential merits of integrating static (offline created) and dynamic (query-specific) document clusters for ad hoc document retrieval. For future work we plan on devising additional integration methods.

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