Diversification Based Static Index Pruning
Application to Temporal Collections

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ABSTRACT
Nowadays, web archives preserve the history of large portions of the web. As media are shifting from printed to digital editions, accessing these huge information sources is drawing increasingly more attention from national and international institutions, as well as from the research community. These collections are intrinsically big, leading to index files that do not fit into the memory and an increase query response time. Decreasing the index size is a direct way to decrease this query response time.

Static index pruning methods reduce the size of indexes by removing a part of the postings. In the context of web archives, it is necessary to remove postings while preserving the temporal diversity of the archive. None of the existing pruning approaches take (temporal) diversification into account.

In this paper, we propose a diversification-based static index pruning method. It differs from the existing pruning approaches by integrating diversification within the pruning context. We aim at pruning the index while preserving retrieval effectiveness and diversity by pruning while maximizing a given IR evaluation metric like DCG. We show how to apply this approach in the context of web archives. Finally, we show on two collections that search effectiveness in temporal collections after pruning can be improved using our approach rather than diversity oblivious approaches.

1. INTRODUCTION
In the past ten years, content producers began shifting to digital media. Consequently, libraries, that aim at preserving cultural artifacts and providing access to them, have begun to shift towards this new media (e.g. archive.org). On the web, preservation implies crawling regularly changing web pages, generating temporal collections called web archives.

The major challenges with these temporal collections are the efficient storage and retrieval of information. Querying these collections requires the use of temporal queries that combine standard keyword queries with temporal constraints. The results of such queries can be obtained by using time-aware ranking models that rank the documents based on temporal and textual similarities [18, 19] or by filtering out the topically relevant documents with time intervals [1].

To efficiently process these queries, information systems rely on an inverted index. It provides a map between terms and their occurrences in the documents. It consists of a collection of postings lists, each associated with a unique term in the collection. Each posting holds some information, typically a document identifier and the frequency of the term in that document.

When querying web archives, the same data structures are used. NutchWAX, an extension to Nutch that uses inverted index data structure, supports full-text search for the Finnish Web Archive for 148 millions of contents (e.g. html pages, pdfs, images etc.), Canada WA for 170 millions of contents, Digital Heritage of Catalonia for 200 millions of contents [17]. As they store the evolving Web, temporal collections require big disk spaces, which in turn leads to big index files that do not fit into the memory. Consequently, the search engine needs lots of disk-accesses, increasing query response time.

To solve this problem, pruning techniques, that compute the results without scanning the full inverted index, were proposed. Index pruning removes postings that are less likely to alter the ranking of the top-k documents retrieved by query execution. Index pruning can be dynamic or static. Dynamic pruning prunes during query processing by deciding which postings should be involved in the ranking process, and whether the ranking process should stop or continue.

On the other hand, static pruning reduces the index size by removing postings from the index offline, independently from any query. It is a lossy index compression technique because it is not possible to bring the compressed data back to its exact uncompressed form. The challenge is to decide which information to prune without decreasing too much the retrieval effectiveness. Obviously, for temporal collections, this decision should take the temporal dimension into account.

However, none of the existing pruning techniques deals with the problem of temporal collections and using existing pruning techniques may lead to loose postings from different time periods. Consider the example of the temporal query “Iraq War in 1991”. If the documents mentioning “Iraq War in 2003” have higher scores than the documents mentioning
"Iraq War in 1991", the index after pruning will have less or no relevant documents for the first temporal query. Ideally, we would like the pruning method to keep the relevant documents for different time periods. Pruned indexes should preserve the temporal diversity of postings.

This issue is related to the problem of search result diversification that aims to improve user satisfaction according to different information needs. Search results should be optimized to contain both relevant and diverse results. A number of search result diversification methods are proposed [30, 2, 10]. We base our work on coverage based diversification, which is an optimization problem of an objective function related to both relevance and diversity of the results. In our case, the objective function is an IR metric adapted to diversification.

As diversification is computationally intensive, we chose to follow a static pruning approach where postings are pruned off-line. To the best of our knowledge, static index pruning and search result diversification were never studied together.

In this paper, we propose a new approach that we name Diversification-based static index pruning.

Although, in our context we focus on temporal coverage, the method can also be applied to non-temporal collections with different diversification categories. The contributions of this paper are the following:

- We take into account diversification in the context of index pruning and propose a variation of the standard greedy algorithm.
- We show how to apply this method to temporal diversification index pruning by defining the temporal aspects associated to a query.
- We perform experiments on two datasets that were modified for the task of retrieval in web archives and show that our approach is stable and works better than other index pruning strategies.

The rest of this paper is organized as follows: Section 2 puts our work into context with related research. In Section 3, we introduce our model for Diversification-based static index pruning. Section 4 shows how to apply our approach to temporal collections. Section 5 describes the series of experiments and analysis. We conclude and discuss future work in Section 6.

2. RELATED WORKS

In ad-hoc information retrieval (IR), the goal is to retrieve most relevant documents according to a topic or query. In order to determine a ranking of documents, a score of relevance is computed for each document. Indexes are used to compute these scores efficiently at query time. As we aim to keep both most relevant and most diverse postings in the index, our work is related to two IR domains, namely Static Index Pruning and Search Results Diversification. Both domains were independently studied, and we discuss them separately in the next two sections.

2.1 Static Index Pruning

Static index pruning reduces the index size by discarding the postings that are less likely to affect the retrieval performance. The seminal work of Carmel et al. [11] was based on two simple ideas: each posting is associated to a score, and a threshold on this score is defined to filter out a part of the postings. The main differences between all the approaches that came latter comes from the way the score and threshold are defined.

In the case of Carmel [11], the score is the TF-IDF value associated with a posting. De Moura et al. [22] proposed to use term co-occurrence information. More recently, Blanco et al. [8] used the the ratio of the probability that a document is relevant to a query over the probability that a document is not relevant to a query (odd-ratio) is used as a decision criteria. We follow a similar approach where every term in the vocabulary is considered as a single term query. Chen et al. [13] proposes to use a measure related to the contribution of a posting to the entropy of the distribution of documents given a term. Thota et al. [27] compare the frequency of occurrences of a word in a given document to its frequency in the collection and use the two sample two proportion statistical test to decide whether to keep a posting or not.

With respect to the thresholds, Carmel et al. [11] defines a threshold that depends on each term in a way that preserves at least the top-k postings of this term (when ranked by their score). A limitation of this approach is that it may retain too many postings for unimportant terms (those that will not be important when ranking documents). In this case, it is possible to use a global threshold (uniform pruning) for all the terms like in [27, 13].

There are other approaches to pruning that are not variations of Carmel’s one [11].

Instead of ranking the postings per term, postings can be ranked by document. Büttcher and Clarke [9] introduced another pruning method that removes the posting lists based on the documents. For each document D in the corpus, the terms of the document are ranked based on their contribution to the Kullback-Leibler divergence between the distribution of terms within the document and the collection. Then, only the postings for the top-k terms in the document are kept in the index.

Another way to prune is to remove whole postings list for a subset of terms or documents. Blanco et al. [7] proposed to remove entire posting list base on informativeness value of a term, in particular inverse document frequency (idf) and residual inverse document frequency (ridf), and two methods based on Salton’s term discriminative model [24], which measures the space density before and after removing a dimension (term). This approach may remove entire terms from the index and should be reserved to a small subset of the vocabulary. Finally, it is possible to fully remove a document from the postings – this is related to the problem of how retrievable a document is [4]. Zheng and Cox [33] suggested an entropy based document pruning strategy where a score is given to each document based on the entropy of each of its terms. Documents below a given threshold are then removed from the index. These types of approaches are orthogonal to ours and could thus be implemented on top of it.

All the works mentioned above focus on different pruning techniques. In our work, we depart from the above approaches since (1) we use an IR metric to select the set of postings that we keep in the index and (2) we try to preserve diverse postings – where diversity is dependent on the task at hand, here searching web archives.
2.2 Search Results Diversification

Result diversification aims to return a list of documents which are not only relevant to a query but also cover many subtopics of the query. The approaches can be classified as explicit and implicit [3].

Implicit methods consist in evaluating a similarity measure between documents and to use this information to select diverse documents by discarding too similar documents. One of the earliest approaches [10], Maximal Marginal Relevance (MMR), select documents by computing a score which is a linear combination of a novelty score (dissimilarity) and the original relevance score. The various approaches based on MMR differ mostly by how the similarity between documents is computed [32, 29].

Explicit methods suppose that the different aspects of a query can be computed along with the extent to which a document is relevant to each of these aspects. The most representative work based on explicit methods is that of Agrawal et al. [2] where the authors propose to maximize the probability of an average user finding at least one relevant result. They assume that an explicit list of subtopics is available for each query. Recently, Welch et al. [30] observed that this approach falls into random document selection after choosing one document for each subtopic.

In the context of index pruning, it is important to reorder all the documents based on diversification. A way to avoid this random document selection is to use a criterion based on the maximization of an IR metric. This type of criterion is used to learn to rank in ad-hoc IR [5, 26] and has recently been applied to diversification [5]. In this latter work, the authors use a performance measure based on discounted cumulative gain, which defines the usefulness (gain) of a document depending on its position. Based on this measure, they suggest a general approach to develop approximation algorithms for ranking search results that captures different aspects of users’ intents. However, no experiments were conducted.

Coverage based diversification corresponds well to our problem of finding temporally diverse results since we can define temporal aspects explicitly as shown in Section 4.3. We want to keep in the index the results that cover many different aspects (e.g. temporal aspects) for the given query. We use the standard greedy algorithm heuristic that we describe in this section.

This heuristic is based on the submodular nature of the function given in Equation 1.

\begin{equation}
S^* = \arg \max_{S \subseteq D, |S| = k} E(M | S)
\end{equation}

If we suppose we can estimate the probability that each individual query \( q \in Q \) is asked, we can compute this expectation as a sum over all the possible queries. This gives:

\begin{equation}
E(M|S) = \sum_{q \in Q} P(q) \sum_{w \in W_q} P(w|q)E(M|q, w, S)
\end{equation}

where \( P(q) \) is the probability of a user issuing query \( q \) and \( P(w|q) \) is the distribution on the aspects of query \( q \) with \( \sum_{w \in W_q} P(w|q) = 1 \). In practice, we assume that the queries are reduced to one term (Section 3.4) and define what (temporal) aspects a query \( q \) is associated with by different means (Section 4.3).

3. Optimization

We now turn to the problem of optimization of Equation 1, which is known to be NP-hard [2, 12]. However, there are known algorithms that give in practice good approximations. In our work, we use the standard greedy algorithm heuristic that we describe in this section.

This heuristic is based on the submodular nature of the function given in Equation 1.

**Definition 1.** Consider a set \( X \) and a function \( f \) defined on \( 2^X \). \( f \) is said to be submodular if for any two subsets \( A \) and \( B \) in \( 2^X \), the following holds:

\[ f(A) + f(B) \geq f(A \cap B) + f(A \cup B) \]

Intuitively, a submodular function satisfies the economic principle of diminishing marginal returns, i.e., the marginal benefit of adding a document to a larger collection is less than that of adding it to a smaller collection [2]. Equation 2 has been shown to be submodular for metrics like DCG [5] that we use in our work.

The greedy algorithm is the most commonly used since it offers guarantees on the objective function value and works well for a wide range of problems. It chooses the best solution that maximizes (or minimizes) the objective function (also known as marginal function or cost function) at each step, independently from the future choices. Finally, all the best local solutions are combined to get the global optimal/suboptimal solution. As proved in [23], the greedy algorithm ensures that the value of the objective function
for the approximation is at least \( (1-1/e) \) times the optimal one.

We adapt the greedy algorithm to Equation 1, as shown in Algorithm 1. The greedy algorithm uses two sets: \( X \) for available items and \( S \) for selected items. \( S \) can be initialized with some items or can be empty. Then, the algorithm iterates over \( X \) and adds the best element (according to the objective) to \( S \) until \( |S| = k \). \( p_i \) that has the highest value for objective function is chosen.

\[
p_i = \arg \max_{p_i} \mathbb{E}(M|S_{i-1} \cup \{p\})
\]

Intuitively, the documents that can cover for many query aspects should be placed in the beginning of the ordering so as to maximize the objective function.

Algorithm 1 Diversify - Greedy Algorithm

**Input:** \( k \) (target), \( S \) the set of all postings, \( f(S') = \mathbb{E}(M|S') \)

**Output:** The set of optimal postings \( S^* \)

1: \( S^* = \emptyset \)
2: while \( |S^*| < k \) do
3: \( p^* \leftarrow \arg \max_{p \in S} f(S \cup \{p\}) \)
4: \( S^* \leftarrow S^* \cup \{p^*\} \)
5: end while
6: return \( S^* \)

### 3.3 Metric family

We use the DCG measure (Discounted Cumulative Gain) [21] as our metric since it is a well-established IR metric that allows an efficient pruning algorithm (Section 3.5) to be defined. DCG can be written as the sum of gain and discount functions as follows:

\[
DCG = \sum_{j \geq 1} c(j) g(d_j)
\]

where \( c(j) \) is a decreasing discount factor\(^1\), and \( g(d_j) \) is the gain function for a document \( d_j \), representing the value of the document for the user. This value is usually defined as a function of the relevance of the document, where the relevance can take several values ranging from 0 (not relevant) to 5 (excellent result). In the following, we suppose that \( M \) belongs to the DCG family.

By choosing a decaying function as a discount function, DCG focuses on the quality of the top-k results. Intuitively, in the context of pruning, choosing a metric \( M \) that has a bias towards top ranked results is interesting since this will help to establish a balance between relevance (adding one more result dealing with the same query aspect) and diversity (adding one more result dealing with another query aspect).

The definition of DCG as a sum over ranks allows to get a closed form formula where the relevance of each document is explicit. Starting from Equations 3, we get:

\[
\mathbb{E}[M|q,w,S] = \sum_{j \geq 1} c(j) \mathbb{E}[g(d_j)|q,w,S]
\]

Since we don't know the relevance of the documents to the query \( q \), we define the expectation \( \mathbb{E}[g(d_j)|q,w,S] \) of the gain as the probability of relevance \( P(d_j|w,q) \) of document \( d_j \) for query \( q \). The probability is directly given by an IR model and it is equal to zero if \( w \) is not an aspect of \( d_j \). Note that we could relax this latter requirement by allowing documents to be more or less relevant given the aspects, but we did not consider this in this work. From Equations 2 and 4, we get:

\[
\mathbb{E}[M|S] = \sum_{q} P(q) \sum_{w \in W_q} P(w|q) \sum_{j \geq 1} c(j) P(d_j|q,w,S) \quad (5)
\]

### 3.4 Query Generation Model

We now turn to the estimation of the distribution over the queries \( q \in Q \). As we work on static index pruning which is applied off-line, we do not have any knowledge over \( Q \). As an approximation like in [8], we assume that each query consists of one single term. More sophisticated strategies would involve using query logs and/or using co-occurrence information, but we leave this for future work.

Starting from Equation 5, we get:

\[
\mathbb{E}[M|S] = \sum_{t} P(t) \sum_{w \in W_t} P(w|t) \sum_{j \geq 1} c(j) P(d_j|t,w,S) \quad (6)
\]

As discussed in Section 3.2, it is shown that the greedy algorithm still achieves \( (1-1/e) \) approximation even in the more general settings of using a submodular function with a logarithmic discount function [5].

We hence use a greedy algorithm to find the best posting to add to the current postings list. The above equation allows us to define an efficient algorithm to find this posting:

\[
P(d_j|t,w,S) = \begin{cases} P(d_j|t) & \text{if } p_{t,d_j} \in S \text{ and } w \text{ matches } d_j \\ 0 & \text{otherwise} \end{cases}
\]

We want to choose the posting that will maximize the criterion of Equation 5. We first define \( \Delta(S,p_{t,d}) \) as the change in the value of the criterion that we would get by adding to \( S \) the posting \( p_{t,d} \notin S \) for a document \( d \) and term \( t \). Let \( l = (d_{t,w,j}) \) be the list of \( N_{t,w} \) documents whose postings \( p_{t,d_{t,w,j}} \) belong to the already selected postings, ordered by decreasing probability of relevance\(^2\) \( P(d_{t,w,j}|t,w) \), and let \( r_{t,w} \) be the first rank where \( p(d_{t,w},t) > p(d_{t,w},t) \).

In this case, adding \( p_{t,d} \) to the posting list will change the rank of all the documents after rank \( r_{t,w} \). Furthermore, the gain of the document \( d \) will be added to the DCG value. All the above allows us to define the increase in DCG as:

\[
\Delta(S,p_{t,d}) = P(t) \sum_{w \in W_t} P(w|t) \times \left[ c(r_{t,w}) P(d|t,w) + \sum_{j = r_{t,w}}^{N_{t,w}} (c(j+1) - c(j)) P(d_{t,w,j}|t,w) \right] \quad (7)
\]

A naive approach to selecting the best posting — e.g. by computing explicitly the list of documents \( l \) would be too computationally expensive. We propose the algorithm 2 that computes the next best posting to select; the overall complexity is given by \( O(\sum_{t \in V} |P_t|^2 |W_t|) \), i.e. the complexity is quadratic with respect to the size of the posting list for a term \( t \) and linear with respect to the number of considered aspects \( W_t \).

\(^1\)Usually set to \( 1/\log(1+j) \) as in this paper

\(^2\)we discard those with a probability 0 as they will not change the criterion
The algorithm 2 shows how to get the next best posting for a given term. At the first round, we need to compute this for each term, but then, for each round of the greedy algorithm, we just need to compute the next best posting for the term corresponding to the posting we just selected. The proposed algorithm is bottom-up, that is, for each term we start from the less relevant documents first, allowing us to optimize the computation of the last sum in Equation 7.

We take as inputs a list of tuples, $P_t$, a set of selected postings $S$, a set of aspects $W$ and a mapping $m$ from the documents to the powerset of aspects $W$. $P_t$ consist of tuples $(d_i, p(t|d_i))$ that contain document $(d_i)$, its score based on the probability of relevance $p(t|d_i)$. $S$ is used to track which postings are already selected. The set of aspects $W$ is a set of tuples $(t_w, p_w)$ where $t_w$ is the number of selected postings and $p_w = p(w|t)$ gives the distribution over the aspects for the given term. Aspects have also associated properties (like the times windows in web archives) but this is not relevant for the algorithm. In the following, we access parts of the tuples by using them as functions, e.g. $d_i(P_t)$ refers to the $d_i$ entry of the $i^{th}$ element of the list.

In the algorithm, each aspect $w$ in $W$ is associated to a state given by $r_w$ and $\Delta_w$, where $r_w$ holds rank position of the current posting $p_{w,t}$ in the list of results associated to aspect $w$. $\Delta_w$ holds the value of the last sum in Equation 7 up to rank $r_w$.

The core of the algorithm is the computation of the Equation 7 (lines 10-16) which combines the relevance score of the document $d_i$ with respect to $p(t|d_i)$ and a diversity score. Starting from the bottom of the list $P_t$ for each document, we traverse each aspect associated to this document. If the document is not selected in the previous execution of the algorithm, its score is calculated according to Equation 7 (line 15) by adding the current $\Delta_w$ to the gain for the document. Otherwise, $\Delta_w$ is updated (line 12) and the current rank $r_w$ is decremented. When we have checked all the list, we can return the best posting along with the change in the criterion (up to the scaling by $p(t)$).

### 3.5 Pruning

There are different ways to estimate the probability $P(t)$ that should reflect how likely a user is to issue the query $t$. We could assume that $P(t)$ is uniformly distributed, but preliminary experiments have shown that this did not work well. Another option would be to use query logs to estimate the probability of a term to occur in a query. However, query logs (with non anonymized queries) are not publicly available.

In this work, we circumvent the problem of estimating $P(t)$ by optimizing each term independently of each other. This amounts at setting $P(t)$ such that we preserve a predetermined number of postings for each term.

Algorithm 3 gives the pseudo-code following this approach. For a given index with vocabulary $T$, we compute the top-$k$ best postings by calling NextBest defined in the previous section. After each call, we update the aspects where the selected posting appear to increment the size of the list associated with the aspects. We keep in the index the top-$k$ postings and discard the other postings. If $k$ is the same for all terms in the vocabulary, it is called uniform top-$k$ pruning.

Our approach can be also used with other pruning methods like the ones proposed in [13, 27] by defining a global threshold $\epsilon$ rather than choosing top-$k$ for each term. In that case, Algorithm 3 would need to be updated, but we don’t detail this in this paper.

### 4. TEMPORAL STATIC INDEX PRUNING

In this section, we show how to use diversification based static index pruning to ensure temporal diversity in temporal collections. Documents and queries are associated to temporal aspects (i.e. a series of time spans). We use [18] as based time model to define temporal aspects and the matching the aspects between documents, queries and the aspects.

We define a temporal aspect as a time window, i.e. a time interval. A query (or a document) can refer to a set of temporal aspects $W_q$ (or $W_d$). While we suppose that the set of temporal aspects for documents is known (e.g. the validity time interval in web archives), this is not the case for queries since we do not know them in advance.

More precisely, given a term $t$, we now need to determine what are its different temporal aspects $W_t$ and their importance by defining a distribution over $W_t$ as discussed in Section 3.1.

In the following, we define three different strategies. The first two are based on fixed-size time windows spanning the entire time range. The only parameter is the duration (size) of time windows. However, this strategy may fail when the term is related to events whose temporal span vary. For example, the term “olympics” depend on the year, on the other hand, the term “earthquake” can take a place any time and

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**Algorithm 2** NextBest($P_t, S, W, m$): Get the next best posting for term $t$

**Input:** $P_t$ list for term $t$ ($d_i, p(t|d_i), t_i$) ordered by decreasing $p(t|d_i)$

$S$ the list of selected postings

$W$ sets of aspects as tuples $(t_w, p_w)$

$m$ a mapping between documents and a subset of $W$

**Output:** Next best posting for term $t$ along with the delta in the criterion

1: $\text{maxdelta} \leftarrow 0$
2: $\text{maxdoc} \leftarrow 0$
3: $r \leftarrow \text{empty map, } \Delta \leftarrow \text{empty map}$
4: for $w \in W$ do
5: $r_w \leftarrow t_w$
6: $\Delta_w \leftarrow 0$
7: end for
8: for $i = |P_t| \rightarrow 1$ do
9: $\text{score} = 0$
10: for all $w \in m(d_i)$ do
11: if $p_{t,d_i} \in S$ then
12: $\Delta_w \leftarrow \Delta_w + (c(r_{w+1}) - c(r_w)) \times p(t|d_i)$
13: $r_w \leftarrow r_w - 1$
14: else
15: $\text{score} \leftarrow \text{score} + (\Delta_w + c(r_w + 1) \times p(t|d_i)) \times p_w$
16: end if
17: end for
18: if $\text{score} > \text{maxdelta}$ then
19: $\text{maxdelta} \leftarrow \text{score}$
20: $\text{maxdoc} \leftarrow d_i$
21: end if
22: end for
23: return ($i, \text{maxdelta}$)
Algorithm 3 Diversified Top-K Pruning

Input: for each term, the desired number of postings \( k_t \), the order list of postings \( P_t \), the set of aspects \( W_t \) and the mappings \( m_t \) between documents and the subsets of aspects.

Output: \( P \) the optimal set of postings

\[
\begin{align*}
1: & \quad P \leftarrow \emptyset \\
2: & \quad \text{for all } t \in T \text{ do} \\
3: & \quad S_t \leftarrow \emptyset \\
4: & \quad \text{while } |S_t| < k_t \text{ do} \\
5: & \quad (i, \Delta) \leftarrow \text{NextBest}(P_t, S_t, W_t, m_t) \\
6: & \quad S_t \leftarrow S_t \cup \{p_t, d_i(P_t)\} \\
7: & \quad \text{for } w \in m_t(d_i) \text{ do} \\
8: & \quad \quad r(w) \leftarrow r(w) + 1 \\
9: & \quad \text{end for} \\
10: & \quad \text{end while} \\
11: & \quad P \leftarrow P \cup S_t \\
12: & \quad \text{end for} \\
13: & \quad \text{return } P
\end{align*}
\]

its time span can vary based on the collection and the magnitude of the earthquake. To handle this case, a dynamic strategy based on a mixture of gaussians is proposed.

In this section, we first present more formally the temporal expressions, and how to match a document to a query, following the work of Gurrin et al. [18]. We then explain in detail our three different strategies to define the temporal aspects \( W_t \) of a term.

4.1 Time Windows

A discrete time model is used to represent the time, according to [18] where a temporal expression \( T \) is represented as

\[ T = (b, e) \]

where \( b \) and \( e \) are respectively the start and end date of the time window. Each is as a time range with a lower bound and upper bound, e.g. \( b = [b_l, b_u] \).

When the temporal expression is uncertain (e.g. “in 2013”), this time representation allows to capture the inherent uncertainty – e.g. \( T = ([1/12/2013, 31/12/2013], [1/1/2013, 31/12/2013]) \) – since we only know the start and end date are in 2013.

While filtering the temporal query results, we need to check if \( d_{time} \) intersects with \( q_{time} \). The intersection operation correspond to a time window where the start (resp. end) date is the intersection of the start (resp. end) date ranges. More formally, let \( l = \max(b_{l_1}, b_{l_2}) \) and \( u = \min(b_{u_1}, b_{u_2}) \). If \( l \leq u \), then the start date of the intersection is the range \([l, u]\), otherwise it is the empty set – and likewise for the end date.

4.2 Document and Query Model

A document \( d \) in the temporal collection \( D \) consists of two different parts: a textual part, denoted \( d_{text} \), and a temporal part, denoted \( d_{time} \). As usual in IR, \( d_{text} \) is represented as a bag of words. Following [18], \( d_{time} \) is represented as a bag of temporal expressions (e.g. publication date) as defined in Section 4.1.

Temporal queries consist of keywords (in \( Q \)) and a set of temporal expressions. The temporal dimension in user input can be embedded in the textual part or not, which gives two types of queries [18]:

- **Inclusive temporal queries**: the temporal dimension of the query is included in the keywords (e.g. “earthquake 17 august 1999”). In this case, the matching is done using standard IR techniques with the date tokens as keywords.

- **Exclusive temporal queries**: the temporal dimension of the query is distinct from its textual part (e.g. “earthquake(\(\emptyset\) 08-17-1999) and is used to filter the results or in ranking function. In this paper, we use a strict filter – i.e. a document either match or not the temporal filter given by the query, but there is no associated score.

4.3 Temporal Aspects Model

We now turn to the problem of estimating the set of temporal aspects given a term/query \( t \), and the distribution \( P(w|t) \), as needed by Equation 6. This is the last part we need to define in order to perform static index pruning.

For each term-query \( t \) in the vocabulary of the document collection \( D \), we can associate a time series, \( S_t \) by identifying all the documents in the temporal collection that contain the term \( t \). Then we take the sum of the term frequencies based on a chosen granularity (e.g. hour, day, week etc.) according to the documents temporal part \( d_{time} \). In our work, we used the day granularity. Figure 1 shows a time series generated for the term ‘disaster’ on Los Angeles Times collection of TREC.

![Figure 1: Histogram for term 'disaster' in Los-Angeles Times (TREC)](image)

4.3.1 Fixed-sized Windows

In this model, the time series of a term is partitioned into equal, fixed sized (\( \gamma \)) windows.

Selecting the correct window size is an important issue for fixed-windows. When a small size is chosen, the number of total windows will increases and this becomes a bottleneck for big data collections. When a big size is chosen, with the decreasing number of windows, we will slowly start to diversify less. In setting the window size, we suppose that each term has a different time pattern. Hence, instead of using an uniform window size for all the terms, we propose to use an adaptive window size for each term, denoted \( \gamma_t \).

There have been many attempts to choose a good bin width for histograms like ours. Scott [25] proposed an approach based on the standard deviation, that was improved by Freedman-Diaconis [16]. The latter work replaces the use of standard deviation with the interquartile range (IQRN),
the distance between the first and third quartile. The Freedman-
Diaconis rule is known to be more robust to outliers, which
is important for us to detect events in our timelines, and
thus we adopted this method. Formally, we use the follow-
ning window size for term \( t \):

\[
\gamma_t = 2IQRN^{-1/3}
\]

The simple window strategy consists in using fixed
sized non-overlapping windows. Formally, a window is rep-
resented as \( w_k = [s + k \times \gamma_t, s + (k + 1) \times \gamma_t] \) where \( s \) is an
offset and \( k \in \mathbb{Z} \). We further assume that \( P(w|t) \) follows
uniform distribution, i.e. \( P(w|t) = \frac{1}{N} \) where \( N \) is the num-
ber of non empty windows.

The sliding window strategy uses overlapping windows
of fixed length. Formally, a window is represented as \( w_k = [s + k/2 \times \gamma_t, s + (k/2 + 1) \times \gamma_t] \). As in the previous model,
we assume that \( P(w|t) \) follows a uniform distribution.

Figure 2 shows simple windows (in blue on the left) and
sliding windows (in green on the right).

4.3.2 Dynamic Windows

In the above models, we considered windows of fixed size.
However, events vary in duration. In the dynamic windows
model we do not force the windows to have a fixed size but
we detect the time windows based on the distribution of the
documents over time.

In order to do this, we use a probabilistic clustering based
on Gaussian mixture models (GMM) of the data distribu-
tion. This probabilistic model assumes that all the data
points are generated from a mixture of a finite number of
Gaussian distributions with unknown parameters. Each distri-
bution can be thought of as a cluster. The probability of
generating a time stamp \( x \) with the GMM is given [6]:

\[
p(x) = \sum_{k=1}^{K} \pi_k N(x | \mu_k, \sigma_k^2)
\]

where the parameters \( \pi_k \) are the mixing coefficients, which
must sum to 1 and \( N(x | \mu_k, \sigma_k^2) \) is a Gaussian distribution
defined by its mean \( \mu_k \) and variance \( \sigma_k^2 \).

A standard methodology consists in using the Expecta-
tion Maximization (EM) algorithm to estimate the finite
the mixture models corresponding to each number of clus-
ters considered and using the Bayesian Information Criteria
(BIC) to select the number of mixture components, taken to
be equal to the number of clusters [15]. The EM algorithm
is an iterative refinement algorithm used for finding maximum
likelihood estimates of parameters in probabilistic models.

Choosing an appropriate number \( K \) of clusters is essential
for effective and efficient clustering. The standard way to es-
imate \( K \) is to start with one cluster and slowly increase the
number of clusters. At each \( K \), the log-likelihood obtained
from the GMM fit is used to compute BIC. The optimal
value of \( K \) is the one with the smallest BIC. In this paper,
this approach is used.

Finally, for each cluster with a mean \( \mu \), variance \( \sigma^2 \) and
weight \( \rho \), we associate a time window \([\mu - \sigma, \mu + \sigma]\) with \( P(w|t) = \rho \).

4.3.3 Smoothing

While we increase the importance of documents associated
with several temporal aspects, we do not want to penalize
too much highly relevant document associated to a few or
only one aspects. In order to do this, we use a smoothing
by defining a new window dubbed the Global window \( G \).
This window contains spans all the time range of term \( t \), i.e.
all the documents belong to the global window. Following
to this, we redefine the distribution of temporal aspects as
follows:

\[
P(G|t) = \lambda_w
\]

\[
P^*(w|t) = (1 - \lambda_w) \ast P(w|t)
\]

5. EXPERIMENTS

In this section we present our experimental evaluation for
the proposed approach. The experiments are conducted by
using two publicly available collections.

Web archive collections are specific due to their temporal
dimension, so time must be present in the test collection
(corpus, relevance judgments etc.). However, there exists no
standard dataset for our experiments because the existing
ones do not contain time-related queries and the judgments
are not targeted towards temporal information.

Two publicly available document collections are used for
our experiments. Both of them have time related informa-
tion, but they differ in their properties, which make them
complementary to evaluate our approach. The first one (LA-
Times) is a standard test collection for static index pruning
experiments [11, 13, 7, 8]. This allowed us to ensure that
our results were in line with those reported in [13, 11]. LA-
Times contains time-stamped documents but no query with
temporal dimension. The second collection (WIKI) is used
in time-aware retrieval model tests. [18, 20]. It contains
queries with time constraints and temporal expressions ex-
ttracted from document but no time-stamped documents:
In the next sections, we briefly present the collections, queries and relevance assessments used to evaluate the methods.

**Baselines**

We compare our approaches Simple, Sliding, Dynamic with the following baselines: the first one is the seminal work of Carmel [11] and the remaining are recent state-of-the-art work on index pruning.

- **TCP** - Static index pruning method presented in [11]
  
  The score of a posting is given by its TF-IDF value in the document, i.e. $tf \times \log(df/N)$ where $tf$ is the number of occurrences of the term in the document, $df$ is the number of documents where term occur, and $N$ is the number of documents in the collection. Then, for each term, the method selects the $k^{th}$ highest score, $z_k$, and sets the threshold value $\tau = \epsilon \times z_k$, where $\epsilon$ is the parameter used to control the pruning rate. Each entry in the term posting list whose score is lower than predefined threshold $\tau$ is considered not important and removed from the posting list. Following [13], for TCP we set $k = 10$ to maximize the precision for the top 10 documents.

- **IP-u** - Static index pruning method presented in [13]

  This approach is based on the notion of conditional entropy of a document conditioned on a term:

  $$H(D|T) = \frac{1}{|T|} \sum_{t \in T} \sum_{d \in D} A(d, t)$$

  where $D$ is the set of documents and $T$ is a set of terms, and

  $$A(d, t) = - \frac{p(d|t)}{\sum_{d'} p(d'|t)} \log \frac{p(d|t)}{\sum_{d'} p(d'|t)}$$

  In their approach, they discard the postings $p_{t,d}$ whose contribution to the conditional entropy $A(t, d)$ is lower than a given threshold. We follow the original settings in [13], and use a Language Model with Jelinek-Mercer smoothing ($\lambda = 0.6$) and use uniform document prior to estimate $p(d|t)$.

- **2N2P** - Static index pruning method presented in [37]

  2N2P uses a two-proportion Z-test, that compares differences between two random samples. In the context of pruning, the authors compare the distributions of a term in the document and in the collection: if they differ too much, then it is necessary to preserve the corresponding posting in the index, otherwise the collection approximation is enough.

  Formally, they compute the statistic

  $$Z = \frac{t_{f_{1,d}} - t_{f_{2,d}}}{E}$$

  where $t_{f_{1,d}}$ is the term frequency in the document $d$ of length $|d|$ and $ct_{f_{1}}$ is the term frequency in the collection $C$ of length (total number of term occurrences) $|C|$. $E$ corresponds to the standard deviation All the postings with a $Z$ score strictly lower than threshold $\epsilon$ are discarded.

**Settings**

Documents are indexed, retrieved and pruned using Apache Lucene\(^3\). Our implementation does not update the document lengths after pruning. The effectiveness is measured with mean average precision (MAP) and normalized discounted cumulative gain (NDCG), two standard metrics in ad-hoc IR [21]. Both are biased towards top-ranked results, but they exhibit a different behavior.

BM25 is used as the scoring function as follows.

$$score(q, d) = \sum_{i=1}^{\min(|q|, |d|)} idf(q_i) \frac{tf(q_i, d)(k_1 + 1)}{tf(q_i, d) + k_1(1 - b + b \frac{|d|}{avgdl})}$$

where

- $tf(q_i, d)$ correlates to the term’s frequency, defined as the number of times that the query term $q_i$ appears in the document $d$.
- $|d|$ is the length of the document $d$ in words (terms).
- avgdl is the average document length over all the documents of the collection.
- $k_1$ and $b$ are parameters, usually chosen as $k_1 = 2.0$ and $b = 0.75$.
- $idf(q_i)$ is the inverse document frequency weight of the query term $q_i$. It is computed by:

$$idf(q_i) = \log \frac{N - df(q_i) + 0.5}{df(q_i) + 0.5}$$

where $N$ is the total number of documents in the collection, and $df(q_i)$ is the number of documents containing the query term $q_i$.

The pruning ratio reported in our results is the percentage of postings in the index removed by the algorithms. When the query contains a time constraint, we use it to filter out documents for which no time window intersect one of the query, i.e. $q_{time} \cap d_{time} = \emptyset$.

5.1 **TREC Los-Angeles Times (LATimes)**

The TREC-LATimes dataset is a standard collection used for index pruning experiments. It consists of randomly selected articles published on the LA Times newspaper in 1989

\(^3\)http://lucene.apache.org/
and in 1990. It contains approximately 132000 articles. For
the evaluation of this dataset we use TREC 6, 7 and 8 ad
hoc topics (topics 301-450). Documents’ publication dates
were used as \(d_{\text{time}}\), but as there was no time associated with
queries and their relevance judgements, we had to generate
them from the original collection.

By using topics 301-450 and corresponding relevance judg-
ments, we created two different datasets. For each topic,
we randomly picked a time interval covered by the dataset
and ran these temporal queries over initial index. The tem-
poral queries that return at least one result with the non-
pruned index were kept for our experiments. By following
this method, we obtained 1000 exclusive temporal short (ti-
tle) and long (title+description) queries for different interval
types: daily queries \(q_{\text{time}} = 1\) day, weekly queries \(q_{\text{time}} = 7\) days and monthly queries \(q_{\text{time}} = 30\) days. Experiments
were conducted with daily, weekly and monthly queries, but
this didn’t lead to changes in results – we thus report weekly
results only.

The first test \(\text{(All relevant Time constraint)}\) is conducted
to check the behavior of our pruning methods. We consider
any document from the specified time period containing at
least one of the keywords to be relevant.

Figure 4a plots MAP and NDCG measures as a function of
the amount of pruning for weekly temporal queries. The first
observation is that for all kind of queries TCP significantly
performs worse than other methods. For queries with prun-
ing ratio smaller than 50%, our three proposed approaches
performs slightly better than others. However, 2N2P does
better at higher pruning level.

In our second test, called \(\text{Time constraint Test}\), documents
out of the time interval are considered as non-relevant but
we kept the original relevance for the documents in the time

Figure 4: LATimes Temporal results

Figure 5: WIKI overall results
interval. As shown in Figure 4b, 2N2P performs better at high pruning level for both long and short queries while our approaches is slightly better at low level pruning. The difference with respect to All related Time constraint Test is that IP-u stays behind TCP and the gap between 2N2P and our methods gets bigger at low pruning level.

As explained before, the temporal queries used in this section do not reflect the real temporal information needs of the users. More precisely, given the random generation of time intervals for queries, they do not favor particularly our approach compared to the others. This is because when the number of associated time intervals become high for each term, diversifying is not optimal. The LATimes collection was used in preliminary experiments to confirm that our approaches perform similarly to the existing ones; the Wikipedia corpus was then used to perform more realistic experiments, as described in the next section.

5.2 English Wikipedia Dump (WIKI)

Although there is an increasing interest in temporal collections and in research related to temporal information, to the best of our knowledge, there is only one available collection with temporal queries and corresponding relevance judgments which takes the temporal expressions in the documents into account. In [18], Berberich et al. used The English Wikipedia dump of July 7, 2009 and obtained temporal queries for this collection by using Amazon Mechanical Turk (AMT). They selected 40 of those queries and categorized them according to their topic and temporal granularity (daily, weekly, etc.). The relevance judgments for these queries were also collected by using AMT and make them publicly available 4.

Time constraints in queries refer explicitly to the time intervals that the relevant wikipedia article refer to. In our experiments, each temporal expressions extracted from documents is considered as the validity interval of the documents and used to filter the results of temporal queries. We used 2330277 encyclopedia articles that contain temporal expressions, and, following [18], considered inclusive and exclusive queries as explained in Section 4.2.

Figure 6a plots MAP and NDCG as a function of the amount of pruning for inclusive and exclusive temporal queries. The results for initial index and the results obtained with topics 301-450 without temporal dimension are coherent with the baseline methods [13, 11]. We can observe that at low pruning levels, the performance can be higher for pruned indexes than with non pruned ones. This just shows that pruning removes postings that would have made non relevant documents retrievable.

We now turn to comparing the different pruning methods. TCP, which performs worst with LATimes collections, significantly outperforms both IP-u and 2N2P. Two of our methods, namely Simple and Sliding, perform better than all the others whatever the query type inclusive or exclusive, and the gap between methods increases with the pruning level. This shows that our time-based diversification method works well.

However, our third method, based on dynamic windows, did not perform as well contrarily to our expectations. It can be related to number of clusters chosen as input for GMM as discussed in Section 4. The clusters obtained did not cover all the documents for some terms - in this case, we chose the closest cluster. In our future works, we plan to investigate further how dynamic windows can be defined, in particular by using other clustering algorithms.

We also investigated the behavior of the pruning methods for queries referring to different temporal intervals (Day, Month, Year, Decade, Century). The dataset was constructed so that each group contains 8 queries. Figure 6 shows the MAP values for exclusive and inclusive queries. We can see that whatever the temporal interval, our proposed approach perform better, but the gap decreases with higher temporal intervals (like year or decade). This is coherent with our approach since when the temporal interval covers a larger time span, diversifying the time aspect of the documents become less important.

6. CONCLUSION AND DISCUSSION

We studied the problem of search result diversification in the context of index pruning. We proposed a new approach called diversification based static index pruning that decides which postings to prune by taking into account both the (estimated) relevance of the documents and the diversification of the results: For each term, we preserve the top-k postings that maximize a chosen IR metric (DCG in this paper) using a greedy algorithm, and discard the rest. In order to perform this pruning efficiently, we proposed an algorithm for selecting the next best posting to preserve.

Our original motivation was to explore index pruning strategies for temporal collections, since these collections are characterized by large index sizes. We thus applied our diversification-based index pruning method to take into account the temporal dimension. This was achieved by associating to each possible term-query a distribution over time windows (time range with a start and end date), based on the time windows associated to each of the documents containing the term at hand. We proposed three different approaches to compute namely Simple, Sliding and Dynamic windows.

Our experiments were conducted on two publicly available collections: LATimes and WIKI. The LATimes collection does not contain the temporal information needs, and was used to show that our approach is competitive with state-of-the-art pruning algorithms. The experiments on WIKI showed that Simple and Sliding methods perform better overall for temporal queries, but we were unable to show good results with the more sophisticated dynamic strategy.

This work is the first one dealing with the (temporal) diversification based index pruning. As such, many different extensions and enhancements of our approach are possible and will be explored in future work.

First, we can explore a better way to estimate the distribution over queries by using query logs, or term co-occurrence information – this would exploit the redundant information that might be contained in two or more terms.

Second, we can explore the behavior of index pruning with more sophisticated time-aware ranking models like those exposed in [18], where the matching between time intervals is not boolean anymore but is real-valued. This approximate matching could be exploited to reduce further the index size.

Finally, one of the challenges in the context of web archives, besides the temporal dimension, is redundancy: Different versions of the same document can be present in the document collections. The changes between the versions are likely to be small for most of documents, and this should be
exploited by keeping only a few (ideally one) of the postings (for the same term) corresponding to the different versions of the document. This would however require the development of a specific test collection based on web archive crawls with related temporal queries and relevance judgements.

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