Document Indexing Aho-Corasick State Machines

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Abstract

The Aho-Corasick algorithm was originally proposed as a bibliographic search mechanism, efficient enough to preclude the construction and maintenance of a search index. As the size of document collections have grown since the development of the algorithm, document collections have grown to the point where cost of rescanning a corpus for every search has become prohibitive and indexing, in some form or another, is an essential optimization for any modern information retrieval system. In this paper we demonstrate the use of Aho-Corasick, not as an alternative to indexing but as a lexical scanning tool employed in the construction of an inverted index. We provide analytic predictions of our indexing algorithm and an empirical evaluation of our inverted index implementation is conducted and the results analyzed. Consistent with our analysis, the hybrid approach yields significant improvement over a naive implementation. In addition, the modular architecture of our indexer allowed the indexing task to be parallelized over multiple physical nodes. The results of parallelization are presented and offer interesting insights towards further horizontal scaling.

Keywords: inverted index, Aho-Corasick state machine, finite automata, pattern matching, parsing

1 Introduction

Information Retrieval is a fast becoming the dominant form of information access, overtaking traditional relational database style searching[3]. The basis of most document retrieval systems is the term-document incidence matrix. This matrix is typically sparse and more efficiently represented as an inverted-index which maps terms to the parts of a document where they occur.

In order to construct an inverted index, documents must be scanned to determine term frequencies. The Aho-Corasick string matching algorithm[1] is a simple and efficient text scanning algorithm. The algorithm constructs a finite state machine to scan for a given set of keywords. It is, in effect, a reduced grammar regular expression parser of the type described in [2]. The algorithm is simple and efficient, construction time being proportional to the sum of the length of the keyword set, and the number of state transitions required to scan a document is independent of the number of the size of the keyword set. Aho-Corasick was originally proposed as a bibliographic search mechanism, efficient enough to preclude the construction and maintenance of a search index. As the size of document collections have grown since the publishing of the Aho-Corasick algorithm, document indexing is essential for efficient document search. In this paper we demonstrate the use of Aho-Corasick, not as an alternative to indexing but as a lexical scanning tool employed in the construction of an inverted index. We provide analytic predictions of our implementation against a naive algorithm and finally, an empirical evaluation of our inverted index implementation is conducted and the results analyzed.

2 Research Plan

The primary goals of this research project is to construct an information retrieval framework within which specific implementations can be evaluated under various operating conditions. To initiate the synthesis of this general framework, a reference implementation will be built, based on the notion of a simple inverted index.

The software architecture of the reference implementation will be carefully documented and follow established design patterns in order to facilitate the future construction of alternative document search schemes within the same framework. The framework will be designed to be executed in a distributed deployment such that it may be used to evaluate the effect of parallelization on a particular algorithm.

The performance of the reference implementation will be tested with respect to the following operating parameters and compared to analytic expectations:

- Number of index keywords
- Number of documents in collection
- Average size of documents

In addition, the reference implementation will be compared against a nave implementation of the inverted indexer. The nave implementation provided a baseline for further evaluation.

3 Design

A black-box functional view of the indexing system is show in figure 1. The system processes a continuous incoming flow of documents and distribute them to parallel indexing threads running on physically separate, heterogeneous nodes. Document queries are performed using an evolving search index. The operational balance is to timeously index new additions to the corpus while servicing concurrent search requests. A view as to how the components of the indexer system are deployed is show in figure 2.

As can be seen in figure 2, the indexer processes are symmetrical and deployed on multiple physical nodes. The individual indexers do not interact directly with one another, making for a simple deployment and operation model. The execution loop of each indexer is as follows:

1. Initialize the indexer by retrieving a collection of index keywords and synonyms from a relational database. These keywords are used to construct a lexical parser which will be used to scan and index documents.

2. Retrieve a batch of unprocessed documents from a relational database. The document batch will be sized according to the physical capabilities of each node. In this implementation, this tuning task is a manual exercise but future enhancements may include an adaptive loading component.

3. Parse each document retrieved and construct an inverted index representing the batch. This *delta* index, as we shall call it, is then used to augment the global index maintained in a relational database.

4. Repeat from step 2.

As shown in figure 2, the searcher component can be executed from any node which has access to the relational database housing the document index. The execution path of a single search query wold be as follows:

1. Canonize search terms based on keyword synonyms defined in the keyword store.

2. Execute a boolean query against the inverted index.

3. Return the list of corpus documents containing the intersection of the canons of the search terms.

4 Experiment Results

The primary goal of this project is to be able to reduce the time to build a document index. As our system is building the inverted index by parsing all documents of the collection, we can expect the time complexity of the task to be proportional to the sum total of characters in the collection. As a result, changing the number of documents or the average size of each document should have a big impact in our time complexity. In addition, our implementation will incur the cost of building the Aho-Corasick state machines used to scan the documents. We can expect the time to build a state machine to be proportional to the sum of the size of the keywords.

Finally we will do a time comparison between our indexer implementation and a naïve implementation. All the time complexities tests are done on a single computer and it is important to understand that all these processes can

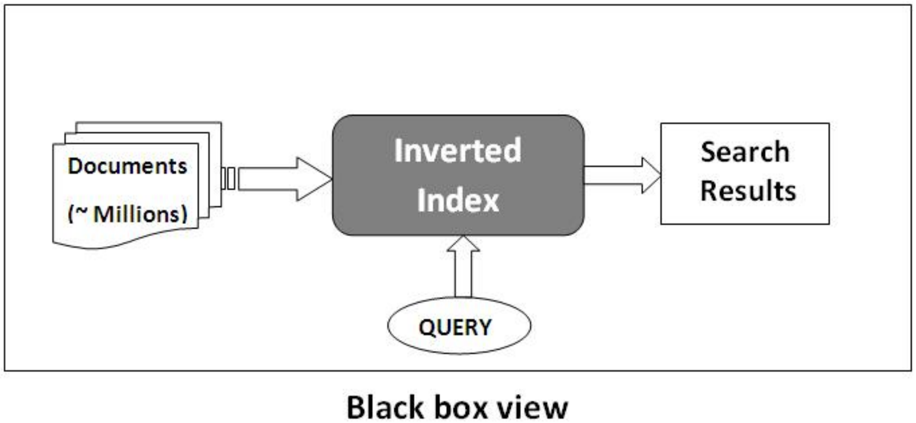

Figure 1: A black-box view of the indexer

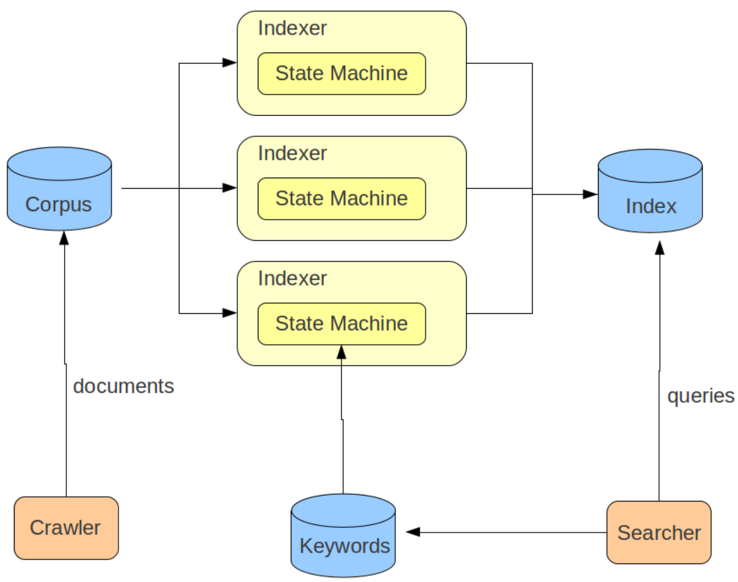

Figure 2: Indexer deployment model

be parallelized. In section 4.5 we install our indexer on multiple computers and explore the performance gain of running parallel instances simultaneously.

All tests were run on a single Intel Core 2 Duo 2GHz processor, 1GB RAM, running a 64-bit Linux 2.6.35 SMP kernel. The Java Virtual Machine used was version 1.6.0-24. The database used was MySQL, running on the same node as the indexer.

4.1 Number of Keywords

To be able to study the impact of different number of keywords, we built a keywords database with 10,000 most popular English words [4]. All the experiments in this part are done with 50,000 posts randomly downloaded from the Internet. The idea is to get a good distribution of documents with respect to length and content. The experiment shown here consist of building the index for different numbers of keywords from the 10,000 keyword database and explore the time and space complexity for the building of the state machine and the building of the index using the state machine.

4.1.1 Time Complexity

- **State Machine Construction:** The time taken to construct the Aho-Corasick state machine was measured for different numbers of keywords. The results of this test is shown in figure 3 and construction time can easily be considered linear with respect to the number of keywords. This is consistent with [1] which proves that the state machine construction algorithm is linearly proportional to the sum of the lengths of the keywords used to construct the state machine.

- **Index Construction:** The time taken for a state machines to build an inverted index of our corpus was measured. The test was repeated using state machines constructed with a varying number of keywords and the results plotted in figure 4. According to [1] which proves that the number of state transitions involved in processing an input string is independent of the number of keywords used to construct the state machine, we would not expect the time complexity to increase with the size of the keyword set. However, as can be seen in 4, the time to build the index increases logarithmically with the number of keywords. This is likely due to the fact that as the number of keywords increases, so does the size of the index and the number of database interacts required to store and update the index.

4.1.2 Space Complexity

As we would have expected it, the space used by the index in the database is proportional to the number of words we are using. It also means that our words have the same probability at the beginning or at the end of our 12,000 word dictionary. This result is reflected in figure 5.

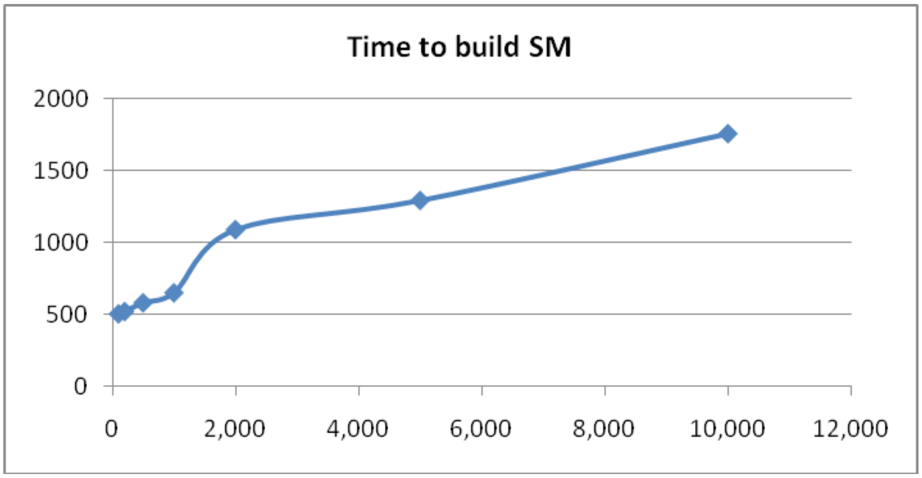

Figure 3: Time to build Aho-Corasick state machine as a function of the number of keywords. Time taken is shown in milliseconds on the y-axis and the number of keywords on the x-axis

4.2 Size of Corpus

To be able to study the impact of different number of Posts, we built a posts database with 400,000 posts randomly downloaded from the Internet. Then the keywords used to build the index are simply the first 5,000 from the previous keywords database.

The experiment shown here consist on building the index for different number of Posts and explore the time and space complexity for the building of the state machine and the building of the index once the state machine is built. We can expect that the time to build the State machine wont change with the number of posts and the time to build the index will increase almost linearly with the number of posts.

4.2.1 Time Complexity

As we were expecting, the time to build the index with the state machine strategy is linear with respect to the number of post, as depicted in figure 6. However, to be able to perform this experiment we had to run the indexer program with batches of 10,000 posts due to Java heap space problems. As a result, the state machine is rebuilt every 10,000 posts.

4.2.2 Space Complexity

As expected, the space used to store the index in the database is proportional to the size of the corpus. This result is shown in figure 7.

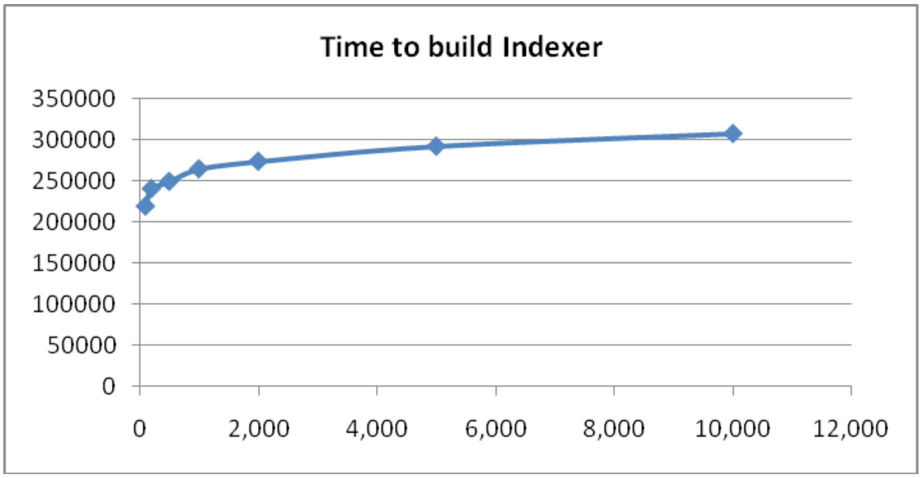

Figure 4: Time to build the inverted index as a function of the number of keywords. Time taken is shown in milliseconds on the y-axis and the number of keywords on the x-axis

4.3 Document Size

As we have seen before, the time to build the index is almost proportional with the number of post. Theoretically this time should be proportional to the total length of all posts. Lets focus on this aspect and study the impact of the length of the post on the time to build the state machine. To do that we built a 5,000 posts database with posts that are all composed of 20,000 characters. Then, we ran our system on different length of substring of these posts.

4.3.1 Time Complexity

- **State Machine Construction:** As expected, state machine construction time does not depend on the length of the documents. Nonetheless it is interesting to compare figures 8 and 9, showing the construction times for the state machine and inverted index relative to the average document size. The comparison shows that state machine construction time is several orders of magnitude smaller than index construction and negligible by comparison. Our state machine is built in 770 ms on average for 1000 keywords with a standard deviation of 18ms.

- **Index Construction:** As expected the time to build the indexer is almost linear with respect to the average document size. This relationship is shown in figure 9.

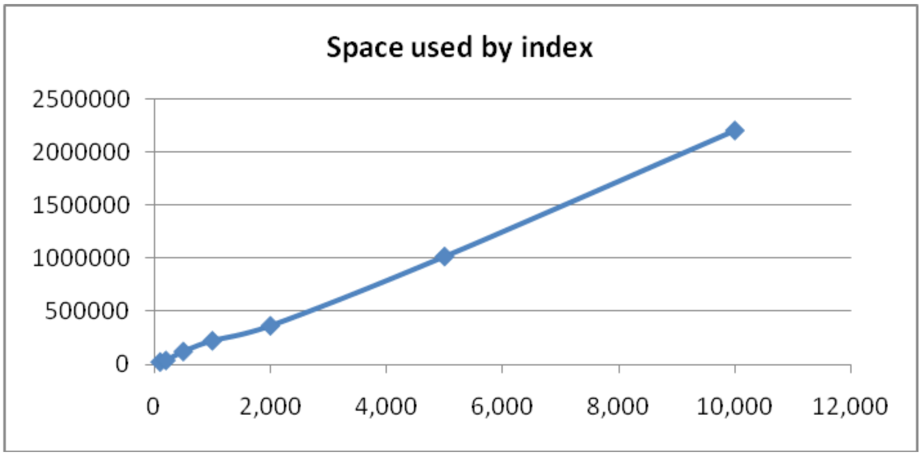

Figure 5: Size of index as a function of the number of keywords. The number of database rows used to store the index is shown on the y-axis and the number of keywords on the x-axis

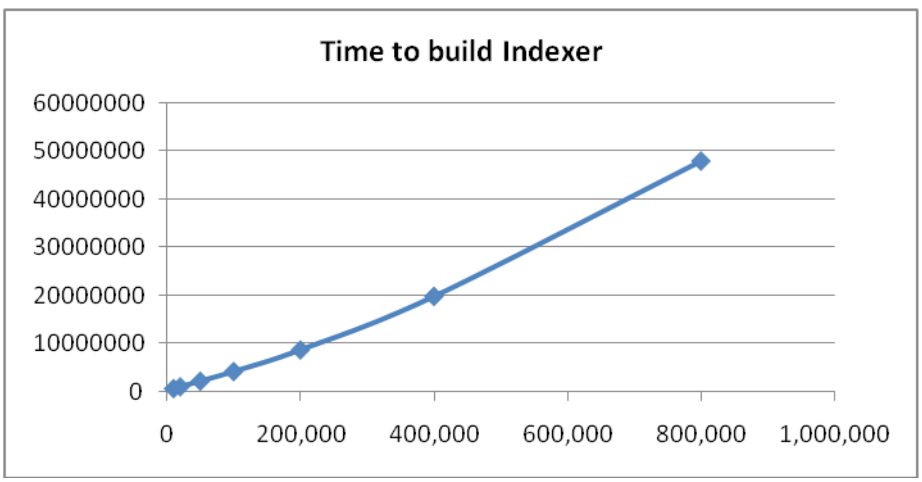

Figure 6: Time to build the inverted index as a function of the size of the corpus. Time taken is shown in milliseconds on the y-axis and the number of documents in the collection on the x-axis

4.3.2 Space Complexity

Here we are studying the number of records in our index database as a function of the average document size. As expected, the larger the documents the more records created to represent the index. However, this is not linear since if a

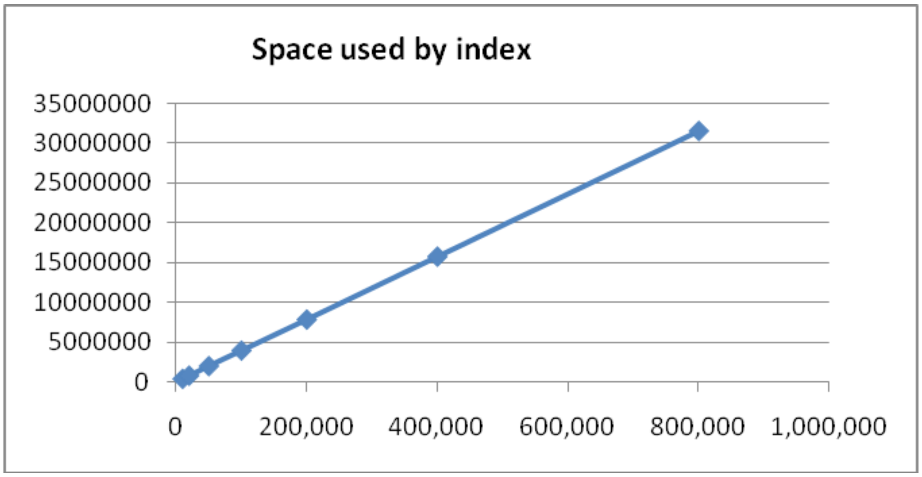

Figure 7: Size of index as a function of the size of the corpus. The number of database rows used to store the index is shown on the y-axis and the number of documents in the collection on the x-axis

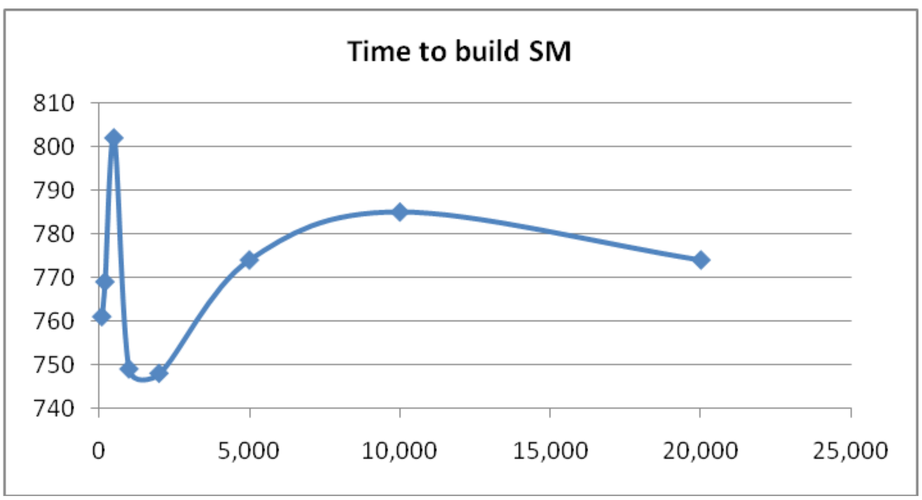

Figure 8: Time to build Aho-Corasick state machine as a function of the average document size. Time taken is shown in milliseconds on the y-axis and the average document size in characters on the x-axis

word occurs many times in the same post we just save it once in the database. This relationship is shown in figure 10.

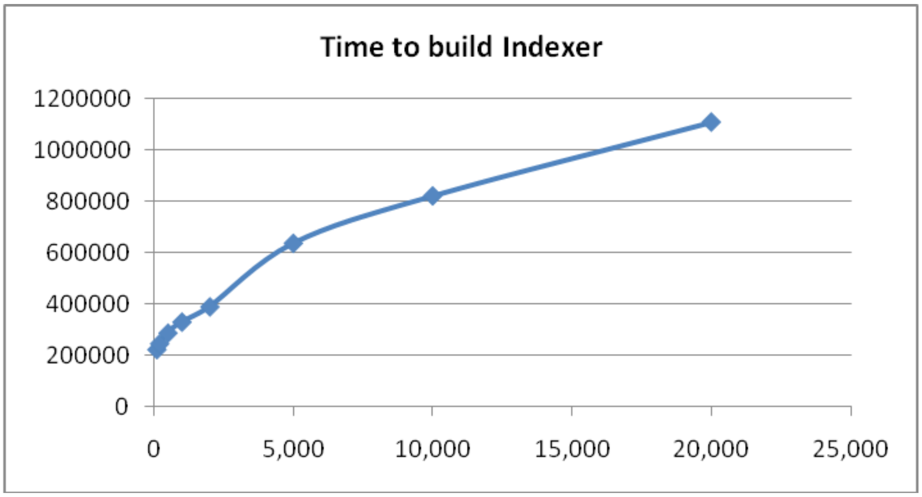

Figure 9: Time to build an inverted index as a function of the average document size. Time taken is shown in milliseconds on the y-axis and the average document size in characters on the x-axis

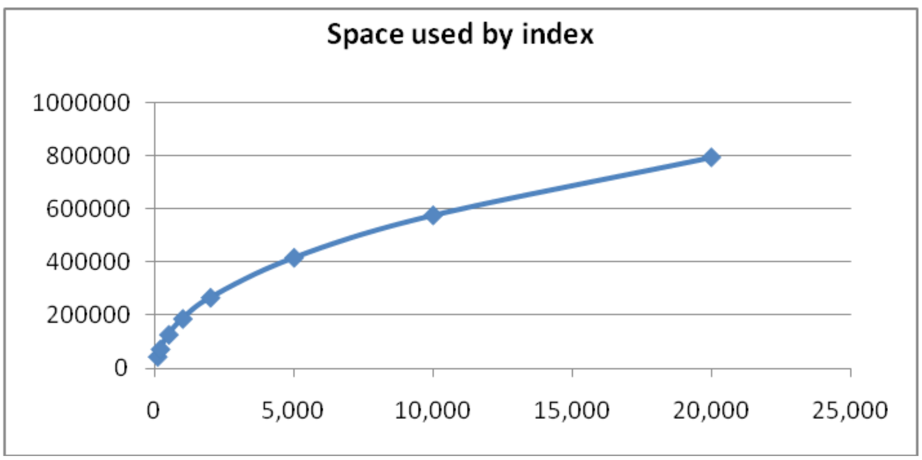

Figure 10: Size of index as a function of the average document size. The number of database rows used to store the index is shown on the y-axis and the average document size in characters on the x-axis

4.4 Comparison with Naïve Index Builder

This part focuses on the improvement that our system with respect to time complexity in comparison with a naïve index builder. The naïve indexer builder has the same input as our system i.e. a list of keywords and a list of documents, and the same output i.e. an inverted index corresponding to the keywords and documents. Algorithm 1 is used in principal for both implementations.

Algorithm 1 Build inverted index

for all *keyword* **do**
  Build a vector v
  for all *document* **do**
    if *keyword* ϵ document **then**
      Add the row (keyword.id, document.id) into v
  end for
  Save v into the database
end for

As we can see this algorithm has a complexity that directly depends on the number of keywords n, the number of document m, and the length of document since we have to check in each document for each keyword. Moreover, we decided to limit, as much as possible, the accesses to the database since it is really time consuming in Java. Thats why we do one access to the database for each keywords and not for each document. In the state machine we do as much accesses to the database as the number of document (in the worst case meaning we find at least one keyword per document). In the following subsections we compare the results for this algorithm with our system results for different number of keywords and posts.

4.4.1 Complexity Analysis

For the naïve algorithm described above, the theoretical worst case time complexity relationship is shown in equation 1.

$$Time \propto keyNum * (docNum * maxLength + conn) \tag{1}$$

where $keyNum$ is the number of keywords, $docNum$ is the number of documents, $maxLength$ is the maximum document length, and $conn$ is the time taken to create a connection to the database. For the state machine algorithm the theoretical complexity relationship is given by equation 2.

$$Time \propto docNum * (maxLength + conn) \tag{2}$$

4.4.2 Document Size

For this experiment we fixed the number of keywords to 1,000 and the number of documents to 5,000 and we ran our code on a database composed of document of different length. The experiment results are shown in figure 11.

As expected, the curves for both our indexer and the naive indexer are almost linear since for the naive implementation:

$$Time \propto (keyNum * docNum) * maxLength + conn * keyNum$$

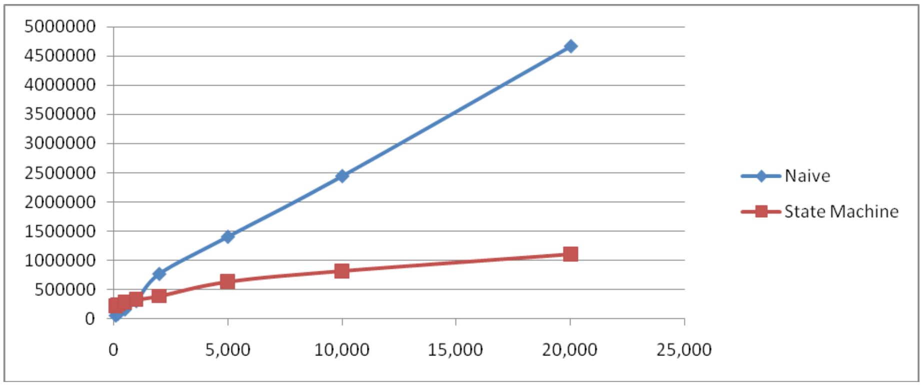

Figure 11: Time to build an inverted index as a function of the average document size. Time taken is shown in miliseconds on the y-axis and the average document size in characters on the x-axis

and for our Aho-Corasick state machine method:

$$Time \propto docNum * maxLength + conn * docNum$$

We can observe that for a small length of document naive method is faster since $keyNum$ is smaller than $docNum$. For $docLength = 1300$ our indexer is far more efficient. To see this effect more clearly, experiment results are plotted on a logarithmic scale in figure 12.

4.4.3 Number of Keywords

As expected, the two implementations exhibit a linear response to the number of keywords used. In the naïve implemementation:

$$Time \propto (keyNum * maxLength) * docNum + conn * keyNum$$

and in our Aho-Corasick state machine method:

$$Time \propto (maxLength + conn) * docNum$$

However, we would have expected the state machine method not to depend on the number of keyword. The reason why its not the case is because when we dont have any keywords in a document, we dont access the database. Knowing that the database access is very time consuming, increasing the number of keyword increases the probability of finding a keyword into each document and so increase the time complexity.

The experiment results are shown in figure 13 and on a logarithmic scale in figure 14.

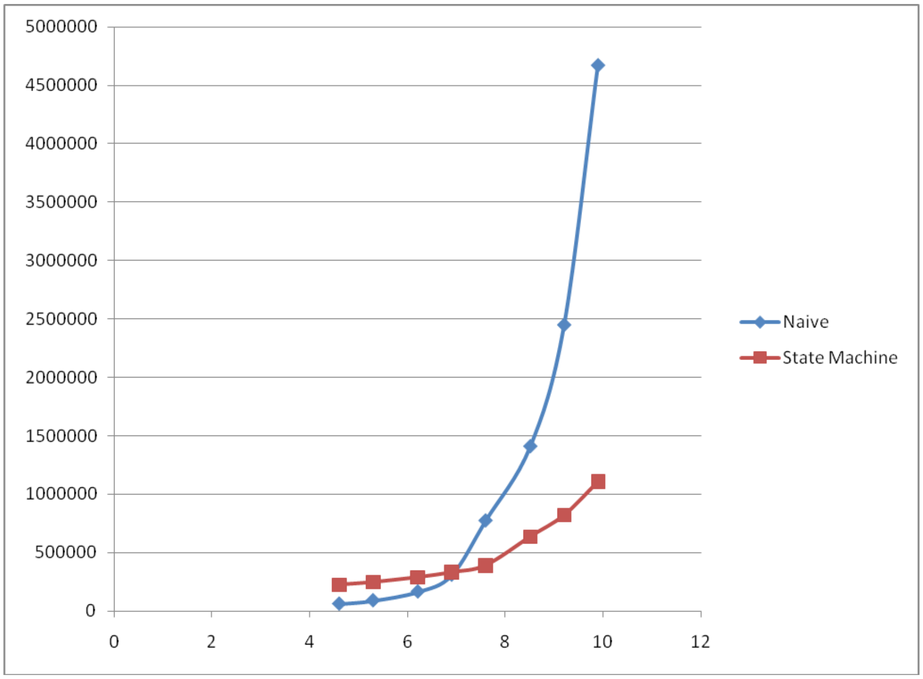

Figure 12: Time to build an inverted index as a function of the average document size. Time taken is shown in milliseconds on the y-axis and the average document size in characters on the logarithmic x-axis

4.4.4 Size of Corpus

As expected, the time complexity is linearly related to the number of documents being indexed. The experiment results are shown in figure 15 and on a logarithmic scale in figure 16. For the naïve implementation:

$$Time \propto (docNum * maxLenght + conn) * keyNum$$

and in our Aho-Corasick state machine method:

$$Time \propto docNum * maxLenght + conn * docNum$$

4.5 Parallelization

Given the modular architecture of our indexer, it is possible to deploy multiple instances of the program to work concurrently on the same indexing task. The instances interact via the database which synchronizes their operations on the corpus and the index itself. To investigate the effect of parallelization on the indexer operation, the indexer was deployed as follows:

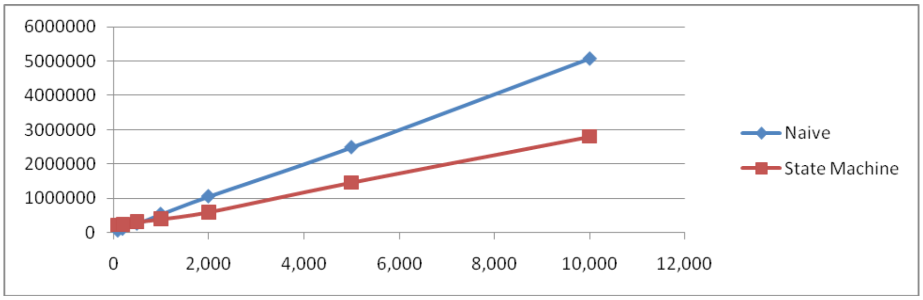

Figure 13: Time to build an inverted index as a function of the number of keywords. Time taken is shown in milliseconds on the y-axis and the number of keywords on the x-axis

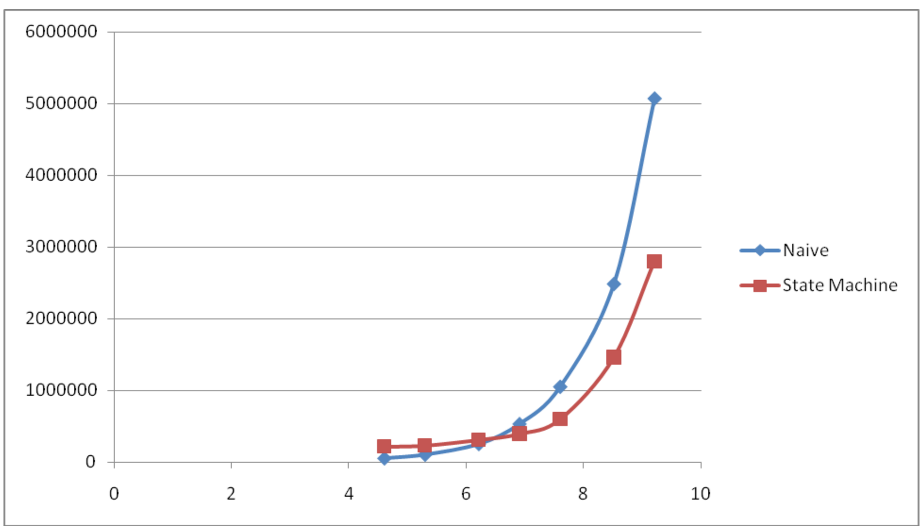

Figure 14: Time to build an inverted index as a function of the number of keywords. Time taken is shown in milliseconds on the y-axis and the number of keywords on the logarithmic x-axis

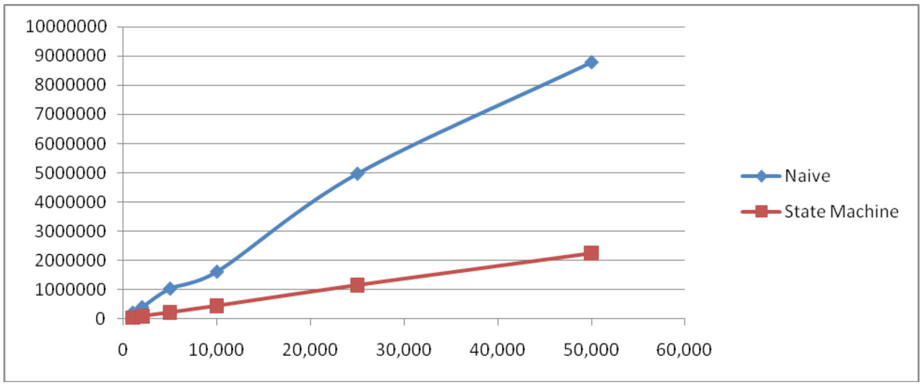

Figure 15: Time to build an inverted index as a function of the number of documents being indexed. Time taken is shown in milliseconds on the y-axis and the number of documents on the x-axis

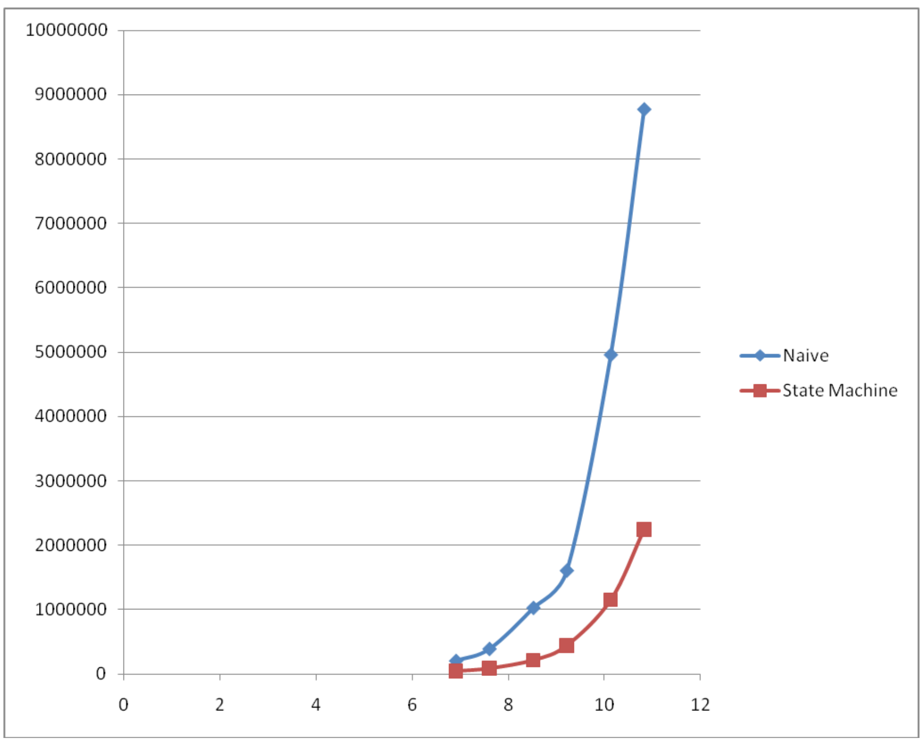

Figure 16: Time to build an inverted index as a function of the number of documents being indexed. Time taken is shown in milliseconds on the y-axis and the number of documents on the logarithmic x-axis

- Single database server storing documents, keywords, and the resulting index.
- Four indexer nodes each running a single instance of the indexer program.

This deployment as well as a description of the sequence of operation are shown in figure 17.

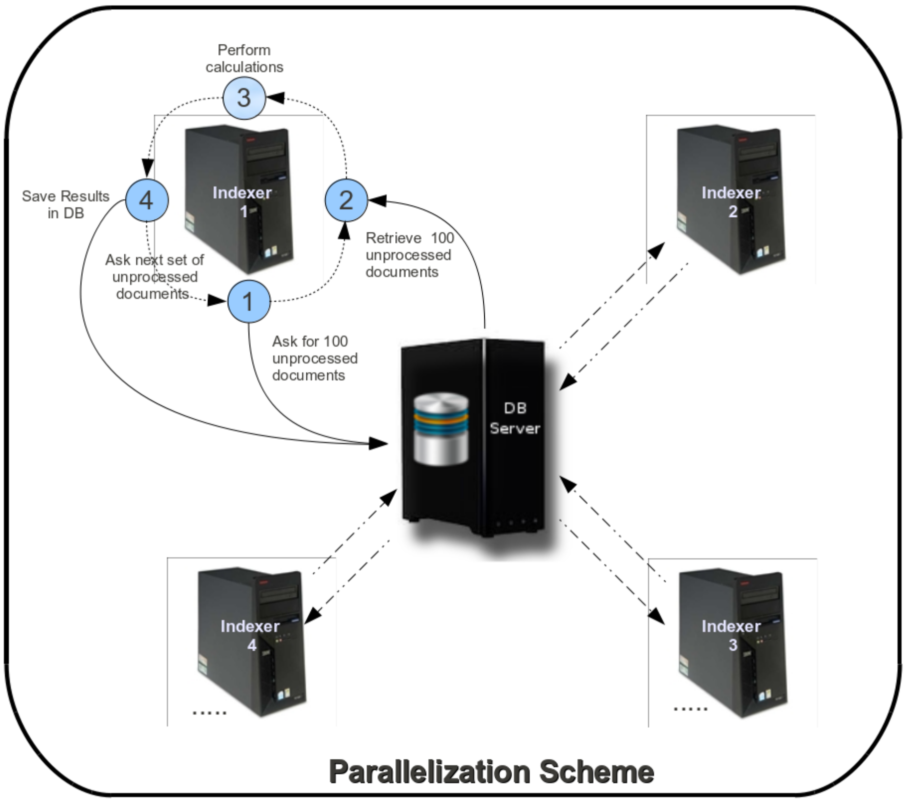

Figure 17: Deployment model of parallel indexer

In this experiment a corpus of 100,000 documents and 1000 keywords were used, each document 5000 words in length. Tests were run using various node combinations and the time taken to index the corpus was measured and normalized to a throughput metric (documents/second) for convenient comparison. Test results using the same number of nodes were averaged to account for differences in the physical capabilities and configuration of the worker nodes. Next, a series of tests was performed using a corpus of 800,000 documents to investigate the effect of corpus size on performance. The results of this experiment are shown in figure 18 and described in detail in the following section.

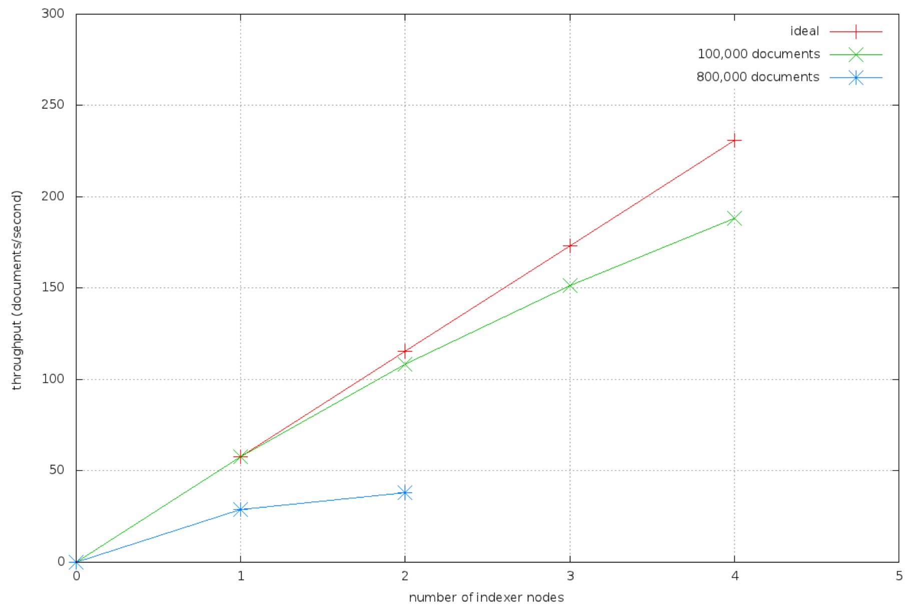

Figure 18: Performance characteristics of parallel indexer deployment. The *ideal* curve shows the theoretical performance curve based on linear combination of average individual node performance over the corpus

4.5.1 Results

For the 100,000 document corpus, increasing the number of nodes increases throughput but with diminishing returns. As the database connection pool is saturated, this becomes the limiting factor of the architecture. If the number of nodes were increased further, one would expect the curve to plateau at some point. After this point, adding additional nodes would offer no improvement and may even decrease performance as the worker processes spend an increasing amount of time context switching and contending for locks. These factors could be mitigated up to a point by increasing batch sizes and tuning the database. However, the characteristics of the curve are ultimately unavoidable in the current architecture.

For the 800,000 document corpus, the performance curve shows an even more severe degradation than the smaller corpus. Since we normalize the performance metrics for the size of the document collection, one would expect this curve to be more similar to that of the 100,000 document collection. A possible explanation for the deviation is that for the larger collection, more documents were present in the database and the resulting index larger. This results in longer table scan times to retrieve and update records. This effect could be alleviated through the use of indices and other database optimization techniques, however, as for the smaller document collection, this degradation is ultimately unavoidable.

5 Conclusions

The experimental results tend to prove what we could expect from theory. Our system is faster than the naïve indexer with respect to the number of keywords being indexed, size of the document collection, and average document size. In particular, our indexer implementation performs relatively well with respect to the number of documents being indexed. Moreover, as soon as we are dealing with a number of keywords that can be representative of real-world needs, the state machine implementation proves also to be significantly faster than the naive indexer.

One of the primary goals of this research project was to leverage the effect of parallelization in reducing the time to index a document collection. We successfully demonstrated that performance gains could be achieved for the indexing task through parallelization as well as the fact that our architecture offers diminishing returns as the number of nodes is increased and as the corpus becomes larger.

Other avenues of interest include, but are not limited to:

- Compare the Aho-Corasick state machine indexer implementation to less naïve indexer implementations.
- Use compression techniques to our algorithm in order to reduce the index size in the database.
- Conduct further parallelization experiments to determine the performance characteristics of our indexer over a wider range of operating conditions.
- Study the time performance improvements possible deploying the Aho-Corasick state machine indexer within a commercial *MapReduce* framework such as *Hadoop*.

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