YASS: Yet Another Suffix Stripper

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Abstract

Stemmers attempt to reduce a word to its stem or root form and are used widely in information retrieval tasks to increase the recall rate. Most popular stemmers encode a large number of language specific rules built over a length of time. Such stemmers with comprehensive rules are available only for a few languages. In the absence of extensive linguistic resources for certain languages, statistical language processing tools have been successfully used to improve the performance of IR systems. In this paper, we describe a clustering-based approach to discover equivalence classes of root words and their morphological variants. A set of string distance measures are defined, and the lexicon for a given text collection is clustered using the distance measures to identify these equivalence classes. The proposed approach is compared with Porter's and Lovin's stemmers on the AP and WSJ sub-collections of the TIPSTER data set using 200 queries. Its performance is comparable to that of Porter's and Lovin's stemmers, both in terms of average precision and the total number of relevant documents retrieved. The proposed stemming algorithm also provides consistent improvements in retrieval performance for French and Bengali, which is currently resource-poor.

1 Introduction

In the Cross Language Information Retrieval (CLIR) road map, discussed by Gey [5] at SIGIR 2002, our attention was drawn towards the challenge of retrieval from languages with poor resources. It was mentioned that the languages of the Indian subcontinent have received very little attention in terms of language specific resource building, although Indian languages are widely spoken in South Asian countries and the population in this part of the world is considerably large. Of the Indic languages, Bengali covers the largest share of Eastern India and is also the state language of Bangladesh. With the proliferation of the Internet in India and Bangladesh over the last decade, the presence of the Bengali community on the World Wide Web has become substantial and significant on-line resources, such as newspapers, webzines, etc have been created. Thus there arises a need for information retrieval from Bengali language documents.

The IR task is generally divided into two major components, indexing and retrieval. While standard indexing and retrieval approaches that have been developed and studied in the context of English language IR may be easily adopted for Bengali, certain language specific components need investigation. The indexing process typically represents the documents as a collection of keywords and their corresponding weights and usually consists of the following steps: (a) tokenization, (b) stopword removal, (c) stemming, (d) phrase recognition and (e) term weighting. Of the above, stopword detection and stemming are language dependent modules.

The words in any natural language text are inflected according to some linguistic rules of that language. Inflection may occur by adding a suffix/affix to the terms or in some cases the entire term may be changed. Stemming aims to identify the morphological classes that share common roots. Most of the existing stemmers use an extensive set of linguistic rules for this purpose. Rule based stemmers for most resource poor languages are either unavailable or lack comprehensive coverage. In this paper, we look at the problem of stemming for such resource poor languages (in particular, for Bengali). Purely unsupervised statistical clustering techniques which do not assume any language specific information are proposed for this purpose.

Bengali is a highly inflectional language where one root may have more than 20 morphological variants. In most cases, variants are generated by adding suffixes to the root word. There also exists a large set of compound words where two roots can join together to form a compound word, and that compound may also have some morphological variants. For example, the word *dhan* means wealth and *haran* means looting or robbing. These two roots combine to form *dhanaharan*, which means robbing of wealth. Now *dhanaharan* can produce morphological variants like *dhanaharankari*, *dhanaharankarider* where *kari* and *der* are standard suffixes.

It may be possible to formulate a set of stemming rules for Bengali that would convert a given word to its stem. However, in view of the nature of the language, this is likely to be a difficult and time consuming process. Further, since a similar task may be needed for other Indic languages, our goal is to eliminate the use of linguistic information, and use a purely corpus based approach instead. We therefore propose a stemming scheme where no linguistic input is considered. We believe this scheme can be adopted for other Indian languages like Hindi, Gujarati etc., as well as English and French, all of which are also primarily suffixing in nature.

We start with a lexicon, extracted from a Bengali news corpus of 50,000 documents. The lexicon contains more than 300,000 terms. A set of string distance measures is defined, and complete linkage clustering is used to discover the equivalence classes from the lexicon. Some infrequent cases arise where clusters correspond to multiple roots and their morphological variants. To choose the most representative canonical form from these multi-root clusters we use some post processing for each cluster. In order to evaluate the effectiveness of the proposed stemming algorithm, we tested its performance on English and French using standard datasets used at TREC and CLEF. The performance of the proposed stemmer was comparable to that of traditional rule-based stemmers, viz. Porter's/Lovin's. Some preliminary experiments with Bengali also yield promising results.

In the following section, we give a brief background on statistical stemming. Sections 3 and 4 present the distance measures we used and the lexicon clustering based approach. Experimental results in support of our approach are given in Section 5. In the last section, we discuss some issues arising out of our work and outline some directions for further study.

2 Background

Stemming is generally considered as a recall-enhancing device. For languages with relatively simple morphology, the influence of stemming is less than for those with a more complex morphology. Most of the stemming experiments done so far are for English and other west European languages ([14], [9]) .

In TREC-4, Buckley [3] demonstrated that a simple stemmer could be easily constructed for Spanish without knowledge of the language by examining lexicographically similar words to discover common suffixes. Goldsmith ([7], [6]) did suffix discovery, employing auto-morphology, a minimum-description-length-based algorithm that determines the suffixes present in a language-sample with no prior knowledge of the language. The frequency of stems and suffixes that would result from every possible breakpoint in each term in a collection was examined. An optimal breakpoint for each token is then selected by applying the constraint that every instance of a token must have the same breakpoint, and then choosing breakpoints for each unique token that minimize the number of bits needed to encode the collection. This "minimum description length" criterion captures the intuition that breakpoints should be chosen in such a way that each token is partitioned into a relatively common stem and a relatively common suffix. Both Buckley and Goldsmith demonstrate the effectiveness of statistical suffix discovery in information retrieval; however, Goldsmith's approach appears to be highly computationally intensive, with execution times for an initial implementation running into days for moderately sized datasets. Very recently, Bacchin et al. [2] validate that the stemmers generated by a probabilistic model are as effective as the ones based on linguistic knowledge.

Oard [13] did suffix discovery statistically from a text collection and eliminated them from the word endings to get the stemmed output. In this experiment, the frequency of end n-grams of the strings was counted (where n = 1,2,3,4) for the first 500,000 words of the text collection. Each instance of every word was considered to get these frequencies. Then, the frequency of the most common subsuming n-gram suffix was subtracted from the frequency of the corresponding (n-1)-gram. For example, the frequency of "ing" was subtracted from the frequency of "ng", as in most cases "ng" occurred as a part of "ing". With these revised frequencies, all n-gram suffixes (n=2,3,4) were sorted in decreasing order. It was observed that the count verses rank plot was convex for English and so the rank at which the second derivative was maximum was chosen as the cutoff limit for the number of suffixes for each length.

Xu et. al. [19] analyzed the co-occurrence of word variants in a corpus to build a stemmer. They refined Porter's stemmer using knowledge from the text collection and observed interesting improvements. This shows that corpus based analysis of word variants can be used to enhance the performance of stemming algorithms. They extended their approach to Spanish and reported improvements in recall. Xu et al. used a variant of expected mutual information to measure the significance of the association of words. Their basic consideration was that word variants that should be conflated will occur in the same documents or in the same text windows (100 words). Their approach split up stem classes created by aggressive stemmers like Porter. The stem classes are re-clustered based on a co-occurrence measure, which is language independent in that it can be applied to any set of stem classes.

In this context, we note that Arabic IR has been receiving increasing attention since TREC 2001. The availability of a test collection has provided a major boost to research and has enabled the formulation of large scale experiments and the investigation of the effects of stemming in quantitative terms. Language resources for Arabic are scarce and applying linguistic knowledge is expensive. Rule based stemmers like Porter's [14] are difficult to customize for this language. This is true for Indian languages also. In order to include these languages in information retrieval services, a generic solution is strongly needed. Statistical approaches have the potential of providing an acceptable solution in this scenario. Statistical techniques exploit word (co-) occurrence patterns in a corpus. Alternatively, related words can be grouped based on various string-similarity measures to infer stemming rules. N-gram based string similarity measures are often used for grouping related words. In Arabic stemming experiments, Roeck [16] used the dice coefficient to measure string distance and clustered them to generate equivalence classes of words in Arabic. Initially affixes were removed using some linguistic knowledge and then terms were clustered. Significant improvement over Adamson's [1] algorithm was observed for the data set considered. Rogati [17] used a machine-learning approach to build an Arabic stemmer. Their scheme is statistical machine translation based, where an English stemmer and a parallel corpus of 10,000 sentences was used for training. Later, monolingual, un-annotated text was used for further improvement. This semi-supervised suffix stripper gives notable improvement for Arabic information retrieval in terms of precision. Larkey [10] extended the approach of Xu and Croft for Arabic stemming.

Ramanathan and Rao [15] report the only work on Indian language (Hindi) stemming. They use a hand crafted suffix list. The suffixes are eliminated from word endings based on some rules. No recall / precision based evaluation of the work has been reported; thus the effectiveness of this stemming procedure is difficult to estimate. In Hindi CLIR experiments done for TIDES (Translation, Detection, Extraction, Summarization) 2003, Larkey et. al. identified a list of 27 suffixes and stripped them from word endings to get the stemming effect. In the surprise language evaluation, they compared both the stemmers and observed that stemming improves the retrieval performance on unexpanded monolingual queries. For the cross-lingual run using query expansion for both English and Hindi, the retrieval performance was poorer than the baseline run.

3 String Distance Measures

Distance functions map a pair of strings s and t to a real number r, where a smaller value of r indicates greater similarity between s and t. We define a set of string distance measures $\{D_1, D_2, D_3, D_4\}$ for clustering the lexicon. The main intuition behind defining these distances was to reward long matching prefixes, and to penalize an early mismatch.

Given two strings $X = x_0x_1 \dots x_n$ and $Y = y_0y_1 \dots y_{n'}$, we first define a Boolean function p_i (for penalty) as follows:

$$p_i = \begin{cases} 0 & \text{if } x_i = y_i \quad 0 \leq i \leq \min(n, n') \\ 1 & \text{otherwise} \end{cases}$$

Thus, p_i is 1 if there is a mismatch in the i-th position of X and Y. If X and Y are of unequal length, we pad the shorter string with null characters to make the string lengths equal. Let the length of the strings be $n + 1$. We now define D_1 as follows:

$$D_1(X, Y) = \sum_{i=0}^{n} \frac{1}{2^i} p_i \tag{1}$$

Our initial investigations suggested that a more effective distance measure could be formulated by considering matches only upto the first mismatch, and penalizing all subsequent character positions. Accordingly, we define D_2, D_3, and D_4 as follows. In the equations below, m denotes the position of the first mismatch between X and Y (i.e. $x_0 = y_0,\ x_1 = y_1,\ \dots,\ x_{m-1} = y_{m-1},$ but $x_m \neq y_m$).

$$D_2(X, Y) = \frac{1}{m} \times \sum_{i=m}^{n} \frac{1}{2^{i-m}} \quad \text{if } m > 0, \quad \infty \text{ otherwise} \tag{2}$$

$$D_3(X, Y) = \frac{n - m + 1}{m} \times \sum_{i=m}^{n} \frac{1}{2^{i-m}} \quad \text{if } m > 0, \quad \infty \text{ otherwise} \tag{3}$$

$$D_4(X, Y) = \frac{n - m + 1}{n + 1} \times \sum_{i=m}^{n} \frac{1}{2^{i-m}} \tag{4}$$

Note that, unlike D_1, the remaining distances do not consider any match after the first mismatch occurs. The actual distances are obtained by multiplying the total penalty by a factor which is intended to reward a long matching prefix, or penalize significant mismatches (or both).

Besides these distances, we also considered the well-known Levenstein or edit distance between strings [11]. This distance counts the minimum number of edit operations (inserting, deleting, or substituting a letter) required to transform one string to the other.

0	1	2	3	4	5	6	7	8	9	10	11	12	13
a	s	t	r	o	n	o	m	e	r	x	x	x	x
a	s	t	r	o	n	o	m	i	c	a	l	l	y

$D_1 = \frac{1}{2^8} + \frac{1}{2^9} + \ldots + \frac{1}{2^{13}} = 0.0077$

$D_2 = \frac{1}{8} \times (\frac{1}{2^0} + \ldots + \frac{1}{2^{13-8}}) = 0.2461$

$D_3 = \frac{6}{8} \times (\frac{1}{2^0} + \ldots + \frac{1}{2^{13-8}}) = 1.4766$

$D_4 = \frac{6}{14} \times (\frac{1}{2^0} + \ldots + \frac{1}{2^{13-8}}) = 0.8438$

Edit distance = 6

0	1	2	3	4	5	6	7	8	9
a	s	t	r	o	n	o	m	e	r
a	s	t	o	n	i	s	h	x	x

$D_1 = \frac{1}{2^3} + \ldots + \frac{1}{2^9} = 0.2480$

$D_2 = \frac{1}{3} \times (\frac{1}{2^0} + \ldots + \frac{1}{2^{9-3}}) = 0.6615$

$D_3 = \frac{7}{3} \times (\frac{1}{2^0} + \ldots + \frac{1}{2^{9-3}}) = 4.6302$

$D_4 = \frac{7}{10} \times (\frac{1}{2^0} + \ldots + \frac{1}{2^{9-3}}) = 1.3891$

Edit distance = 5

Figure 1: Calculation of various distance measures

In Figure 1, we consider two pairs of strings $\langle$*astronomer*, *astronomically*$\rangle$ and $\langle$*astronomer*, *astonish*$\rangle$ as examples. The values of the various distance measures for these pairs are shown in the figure. According to D_1, D_2, D_3, and D_4, *astronomer* and *astonish* are farther apart than *astronomer* and *astronomically.* This agrees with our intuition. However, the edit distance is lower for the second pair. This example suggests that the new distance measures may be more suitable for our purpose than the traditional edit distance.

4 Lexicon Clustering

The distance functions defined above are used to cluster words into homogeneous groups. Each group is expected to represent an equivalence class consisting of morphological variants of a single root word. The words within a cluster are stemmed to the 'central' word in that cluster. Since the number of natural clusters is unknown a priori, partitional clustering algorithms like k-means are not suitable for our task. Graph-theoretic clustering algorithms appear to be the natural choice in this situation because of their ability to detect natural clusters in the data.

Three variants of graph theoretic clustering are popular in literature, namely, *single-linkage*, *average-linkage*, and *complete-linkage* [8]. Each of these algorithms is of hierarchical (agglomerative or divisive) nature. In their agglomerative form, the cluster tree (often referred to as a dendrogram) consists of individual data points as leaves which are merged to form groups of points at higher levels. The groupings at each level represent a clustering of the data. In all the above three algorithms, two most 'similar' groups of points (possibly singletons) are merged at each level. The algorithms differ in the way the similarity between the groups is defined.

In the single-linkage method, the similarity between two groups is defined as the maximum similarity between any member of one group and any member of the other group. The groups only need to be similar in a single pair of members in order to be merged. Single linkage clusters can be long and branched in high-dimensional space and the merging criterion often causes “chaining”, where a single element is continually added to the tail of the biggest cluster. Single linkage clustering can be obtained by constructing a minimal spanning tree of the data points and recursively deleting the heaviest edges to obtain the desired number of clusters.

In the average linkage method, the similarity between two groups of points is defined by the mean similarity between points in one cluster and those of the other cluster. In contrast to single linkage, each element needs to be relatively similar to all the members of the other cluster, rather than just one. Average linkage clusters tend to be relatively round or ellipsoid. Average linkage can be approximately computed quite cheaply by considering the similarity between the means of each cluster (if they can be computed).

In the complete-linkage algorithm, the similarity of two clusters is calculated as the minimum similarity between any member of one cluster and any member of the other cluster. Like single-linkage, the probability of an element merging with a cluster is determined by a single member of the cluster. But in this case, the least similar member is considered instead of the most similar. In other words, the merged cluster has the smallest possible diameter. Consequently complete linkage clusters tend to be very compact. Complete-linkage clustering can also be described in terms of a clique. Let d_n be the diameter of the cluster created in step n of complete-linkage clustering. Define graph $G(n)$ as the graph that links all data points with a distance of at most d_n. Then the clusters after step n are the cliques of $G(n)$. The nature of the lexicon suggests that the most compact clusters would be useful. Thus, we choose the compete-linkage algorithm for our experiments.

Determining the Number of Clusters

As mentioned above, in graph theoretic clustering methods, the clusters are obtained by deleting the heaviest edges of the cluster tree. In other words, all edges above some threshold may be deleted to obtain the desired number of clusters. There is an inverse relation between the chosen threshold and the number of clusters generated. A high threshold results in a small number of clusters, each of which is relatively large. Conversely, a low threshold results in a larger number of relatively small clusters.

Obviously, the choice of threshold is an important issue. If a high threshold is chosen, we get an aggressive stemmer, which forms larger-than-actual stem classes, where semantically unrelated forms are conflated erroneously. If the chosen threshold is too low, we get a lenient stemmer, which fails to conflate related forms that should be grouped together. Thus, choosing a threshold which results in clusters that accurately represent the true stem groups is the basic challenge in case of cluster based stemming.

In our experiments (see the next section), we find a suitable edge-weight threshold empirically. Given a lexicon, we first compute the number of clusters generated at various threshold values. This gives us a number-of-clusters vs. threshold curve. Next, we look for step-like regions in this curve. A *step* is a region where the curve flattens out, i.e. the number of clusters does not change much as the threshold value is changed. A threshold θ is then chosen from such a region as a candidate threshold for generating the desired stem classes.

Figures 2 and 3 show the variation in the number of clusters with threshold value using the string distances D_1, D_2, D_3, D_4 defined previously. The lexicon used to generate these graphs was constructed from the WSJ documents on TIPSTER disks 1 and 2. If the number of clusters changes by less than 10 for 2 successive threshold points on the x-axis, we regard this portion of the curve as a step. It turns out that these curves have multiple steps and therefore, multiple candidate threshold values may be obtained from each curve. These candidate values are used in our experiments reported in the next section.

5 Experiments

The primary goals of our experiments were the following:

Expt. 1. to choose the most effective distance measure from D_1, D_2, D_3, D_4, and to determine a threshold value θ that results in good retrieval performance when used with this measure in the clustering step;

Expt. 2. to verify that the proposed stemming method does indeed yield improvements in retrieval performance;

Expt. 3. to compare the performance of the proposed stemmer with traditional algorithms such as Porter's for the English language; and

Expt. 4. to study how well the method works for other languages, viz. French and Bengali.

For these experiments, a test collection is needed. While standard test collections are available for English, no such test collection is available for Bengali. Motivated by the nature of test corpora commonly used for IR experiments, we have recently constructed a corpus of about 50,000 news articles taken from the most popular Bengali daily in India. This collection has been described in more detail by Majumder et al. [12]. The collection has been supplemented by 25 queries. We are in the process of collecting relevance judgements for this query set using the pooling approach used at TREC. The absence of comprehensive relevance judgements precludes the possibility of using the Bengali data for the entire set of experiments, even though our investigations were initially motivated by the need to construct a stemmer for Bengali. Also, since no stemmer for Bengali exists, the only baseline that we can compare with is a retrieval run that uses no stemming.

We therefore decided to tune and evaluate the stemmer (experiments 1–3 above) using a standard English collection. Accordingly, we chose the WSJ and AP collections from TIPSTER disks 1 and 2, and TREC queries 1-200 for our primary experiments. The size of these corpora and the corresponding lexica are shown in Table 1. Finally, for experiment 4, we also conducted some runs on Bengali (using our data) and French

Corpus	Size (MB)	# documents	Size of lexicon
AP	497	164601	262128 words
WSJ	514	173252	179387 words

Table 1: Size of English corpora used in our experiments

(using the LeMonde dataset from CLEF). The results of these experiments are presented below.

5.1 Expt. 0: Baseline strategies

We use the SMART system [18] for all our experiments. For the baseline run, queries and documents were indexed without any stemming. Stopwords were removed, however. The Lnu.ltn [4] weighting strategy was used. We then indexed the documents and queries using (in turn) two conventional stemmers for English: Porter's and Lovin's. SMART uses a version of Lovin's stemmer by default. As most of the literature refers to Porter's stemmer, we also incorporated Porter's stemmer within SMART. Additionally, we implemented a stemmer described by Roeck [16] that is also clustering-based, but which uses an n-gram based string similarity measure.

5.2 Expt. 1: Distance measure and threshold selection

Next, we integrated the four clustering-based stemmers within SMART. Our first set of experiments was intended to help us choose the most effective distance measure along with an appropriate threshold value for use in subsequent experiments. For these experiments, we used only the WSJ sub-collection and TREC

D1					
θ	**0.023**	**0.046**	**0.069***	0.104	0.138*
AvgP	**0.3634**	**0.3732**	**0.3677**	0.3469	0.3367

D2					
θ	**0.21**	**0.31**	**0.41***	0.54*	0.61*
AvgP	**0.3675**	**0.3721**	**0.3600**	0.3403	0.3401

D3					
θ	1.15*	1.35	1.55*	1.75	2.15*
AvgP	0.3748	0.3787	0.3796	0.3785	0.3727

D4					
θ	**0.56***	**0.71***	**0.86***	**1.01**	1.16
AvgP	**0.3650**	**0.3662**	**0.3775**	**0.3726**	0.3396

Table 2: Retrieval results for various distance measures and thresholds on (WSJ, queries 151-200)

queries 151-200, with the hope that a threshold value learned from this dataset would be stable enough to be used on other datasets as well (see the end of this section for verification).

For each of the distances D_1, D_2, D_3 and D_4, we considered 5 different clustering thresholds for a total of 20 retrieval runs. Table 2 shows the mean average precision obtained for each of these retrieval runs. The initial set of threshold values that we tried corresponds to the mid-points of step-like regions in Figures 2 and 3. These have been marked with a * in Table 2. The remaining threshold values were added at roughly equal intervals before, in between, or after the initially chosen values.

The results for each distance measure were analyzed using the Tukey HSD test. Based on this test, the results can be roughly separated into two categories for D_1, D_2 and D_4. For example, when using D_2, setting θ to 0.21, 0.31 or 0.41 yields significant improvements compared to using the other two values of θ. However, the differences between these three runs were not found to be significant. Likewise, for D_4, results obtained using $\theta = 0.56, 0.71, 0.86, 1.01$ were not significantly different, but setting $\theta = 1.16$ caused a signficant degradation in performance. Interestingly, for D_3, no significant differences in retrieval performance were found for the range of threshold values used.

Table 3 presents a comparison of the various distance measures. A suitable threshold value is chosen for

	No stemming	$D_1 - 0.046$	$D_2 - 0.31$	$D_3 - 1.55$	$D_4 - 0.86$	Lovins	Porter	n-gram
Rel ret	3082	3235	3249	3268	3265	3318	3290	3171
P_{20}	0.4920	0.5020	0.4960	0.5090	0.5130	0.5030	0.5060	0.4960
Avg.P	0.3505	0.3732	0.3721	0.3796	0.3775	0.3746	0.3746	0.3595

Table 3: Retrieval results for various stemmers on (WSJ, queries 151-200)

$\theta \rightarrow$	No-Stem	1.35	1.55	2.15
Rel Ret	3887	4140	4133	4130
P_{20}	0.4740	0.4940	0.4900	0.4960
Avg.P	0.3514	0.3762	0.3776	0.3771

Table 4: Performance of D_3-based stemmer at different clustering thresholds on (AP, queries 151-200)

each measure based on the results in Table 2. The results of the baseline (no stemming), Porter, Lovins and n-gram based runs are also included for comparison. The differences in the effectiveness of the 4 distance measures were not found to be significant, but since D_3 seems to be the least sensitive with respect to variations in the threshold value, we choose this measure for our subsequent experiments.

Our next goal is to study the stability of the threshold chosen above. We therefore test the D_3-based stemmer using a different collection, viz. the AP articles from TIPSTER disks 1 and 2 (the query set remains the same). Table 4 summarizes the results obtained using the D_3 based stemmer at various clustering thresholds for the AP dataset. Once again, the performance of the stemmer is not significantly affected by the choice of threshold; in particular, $\theta = 1.55$ appears to be an acceptable choice for this dataset also. An examination of the number-of-clusters vs. threshold curve for the AP lexicon (see Figure 4), shows that there is a "step" between $\theta = 2.00$ and 2.25. From Table 4, it is clear that a threshold value chosen from this step would also be acceptable for this dataset.

5.3 Expts. 2 and 3: Comparison with baseline strategies

The next set of experiments compares the performance of the D_3-based stemmer with the baseline strategies (no stemming, and Porter's stemmer). For this comparison, we use TREC queries 1-200 with both the AP and WSJ collections from TIPSTER disks 1 and 2. The results are summarized in Table 5. Figure 5 shows the same comparison graphically.

WSJ

	No stemming	D_3	Porter
Rel ret	16831	17245 (+2.5%)	17236 (+2.4%)
P_{20}	0.5293	0.5368 (+1.4%)	0.5340 (+0.9%)
Avg.P	0.3647	0.3811 (+4.5%)	0.3789 (+3.9%)

AP

	No stemming	D_3	Porter
Rel ret	16241	16732 (+3.0%)	16805 (+3.5%)
P_{20}	0.4732	0.4857 (+2.6%)	0.4895 (+3.4%)
Avg.P	0.3799	0.3916 (+3.1%)	0.3956 (+4.1%)

Table 5: Performance of D_3-based stemmer for TREC queries 1–200

In terms of overall performance, our stemmer and Porter's both yield comparable improvements over the baseline (no stemming). The difference in mean average precision for the baseline and D_3 runs was found to be statistically significant (paired t-test, 200 observations, $P = 0.0026$ for AP, $P = 1.2 \times 10^{-6}$ for WSJ). In contrast, the difference in performance between the D_3-based and Porter's stemmers was not significant (paired t-test, $P = 0.23$ for AP, $P = 0.27$ for WSJ). We repeated the tests of significance using the number of relevant documents retrieved for each query (instead of the average precision), and reached the same conclusions.

5.3.1 Query-wise analysis of results

To better understand the difference between the two stemmers, we do a query-by-query analysis of the results. Table 6 shows the number of queries for which each method outperforms the other (in terms of average precision). The numbers in parentheses indicate the number of queries for which the performance of the two stemmers differs by more than 5%.

WSJ		**AP**	
D_3 better	Porter better	D_3 better	Porter better
98 (40)	102 (36)	89 (26)	103 (41)

Table 6: Queries for which performance differs by > 5%

We manually examined some of these queries where the performance variation was large. Query no 128 (Privatization of State Assets) is an example where the D_3 stemmer achieves an average precision of 0.3381, and retrieves 211 relevant documents. The corresponding figures for Porter's stemmer are 0.2296 and 175. The total number of relevant documents for this query is 296. The key to the performance difference lies in that fact that Porter's stemmer conflates both the query terms "privatization" and "private" to "privat". Because of such aggressive stemming, a specific term like "privatization" (which happens to be important for this particular query) is conflated to a more general term, and gets a low idf (inverse document frequency) value. In contrast, D_3 assigns these words to different clusters. As a result, the query is indexed using the more specific term "privatization". Of course, it is possible to construct examples where conflating "privatization" and "private" would be beneficial. In such cases, Porter's stemmer would perform better than D_3.

Query 26 (Tracking Influential Players in Multimedia) is one such example. This query contains the word "develop". At $\theta = 1.55$, D_3 places "develop" and "development" in two separate clusters, whereas Porter correctly places them in the same equivalence class. As expected, relevant documents containing the word "development" are ranked more highly by Porter's stemmer than D_3. Likewise, for query 75 (Automation), Porter's stemmer converts "automation", "automate", and "automated" to "autom", while D_3 places these words in two separate clusters.

One general problem with Porter's stemmer (as far as retrieval is concerned) is that it does not seem to strip the possessive marker *'s* from the end of words[1]. Likewise, words like "largest" and "strongest" are not converted to "large", "strong".

Overall, the table above shows that in a large set of sample queries, the honours are about equally divided between the two methods. This is also in keeping with the results of the t-tests reported above.

5.4 Expt. 4: Performance on French and Bengali data

5.4.1 French Run

For these experiments, we used the LeMonde94 text collection, along with 50 French topics (41 to 90) designed for this corpus. This data is available as a part of the CLEF dataset. We conduct three retrieval runs: the first does not use stemming, the second uses the French version of Porter's stemmer available from *http://snowball.tartarus.org/*, and the third uses the D_3 based stemmer.

As in the case of English, the issue of threshold selection has to be addressed. In accordance with the strategy suggested in Section 4, we first plot the number-of-clusters vs. threshold curve (Figure 6) to identify a suitable threshold for clustering the lexicon. Three prominent steps are observed around $\theta = 1.15, 1.55, 2.10$. The results for all the runs are shown in Table 7.

	No stemming	$D_3(1.15)$	$D_3(1.55)$	$D_3(2.10)$	Porter
Rel ret	516	540	538	538	540
P_{20}	0.2222	0.2611	0.2578	0.2522	0.2467
Avg.P	0.3987	0.4301	0.4334	0.4153	0.4284

Table 7: Performance of D_3-based stemmer on the French LeMonde corpus

We first observe that a threshold of 1.55 works well for this collection as well. As in the case of English, the D_3 based method yields significant improvements in performance over the baseline (paired t-test, 45 observations[2], $P = 0.03$). Also, its performance is comparable to that obtained using the Porter's stemmer (paired t-test, 45 observations, $P = 0.73$).

[1]The version of Porter's stemmer that is available from *http://snowball.tartarus.org/* does not do this.
[2]Since there were no relevant documents for 5 queries, the evaluation was based on 45 (rather than 50) queries.

5.4.2 Bengali Run

Unlike English and French there is no available relevance judged corpus for Bengali. In general there are few available language resources for the Indian languages. We constructed a corpus containing news articles from the most popular printed Bengali daily in India, Anandabazar Patrika (ABP). The Bengali alphabet set is larger than English and it has about 49 characters. The size of the Bengali lexicon extracted from the ABP corpus was 301562 words. The Bengali lexicon is then clustered using complete-linkage agglomerative clustering. Once again, for clustering the Bengali lexicon, we choose D_3 as our distance measure.

A stopword list for Bengali was constructed by taking the 500 most frequent terms from the lexicon and then manually identifying a list of 354 words from the whole set. The stopwords thus selected were mostly articles and indeclinables, prepositions and conjunctions. Interestingly, nouns like *Budhbar* (Wednesday) and Kolkata (Calcutta) were among the top 500 terms, although we did not include them in the stopword list. For all the runs the stopwords were removed first. We constructed 25 topics in Bengali with Title and Narration fields and retrieved 20 documents using the title only. The average title length in terms of words is 4.4. Since comprehensive relevance judgements were unavailable, we manually judged the top 20 documents per query and measured the precision for this set (P_{20}).

We start by adopting the same threshold value (1.55) that works well for English and French. For further clues, we examine the number-of-clusters vs. threshold curve for Bengali (see Figure 7). The curve has several step-like regions, with a fairly long step around 0.55. We also perform a retrieval run with this threshold. We could have chosen points from the remaining steps also, but this was skipped since precision has to be manually measured for every point. The results for these runs are shown in the table below.

	Unstemmed-run	Stemmed-run@1.55	Stemmed-run@0.55
Rel ret	178	216 (+38)	248 (+70)
P_{20}	0.3560	0.4320 (+21.3%)	0.4960 (+39.3%)

Table 8: No of Relevant documents and P_{20} in Bengali runs

The unstemmed and stemmed runs at 1.55 and 0.55 retrieve 178, 216 and 248 relevant documents respectively. The stemmed runs thus retrieve 39 and 70 more relevant documents (an average of 1.3 and 2.33 more relevant documents per query). The relative improvement observed using stemming for Bengali is 21.3% and 39.3% respectively. These improvements were found to be statistically significant (paired t-test, 25 observations, P-value (1-tail) = 0.010 and 0.004 respectively). Thus, for a highly inflected language like Bengali, stemming substantially improves the retrieval effectiveness.

The table also suggests that, while $\theta = 1.55$ works well for both English and French, better results may be achievable for Bengali with a lower threshold. This is not entirely surprising since Bengali and English orthography are different by nature. However, a detailed investigation of this issue — threshold selection for Bengali and related languages (e.g. Assamese, Oriya) — will have to wait until comprehensive datasets are available in these languages.

6 Conclusions and Future Work

With the worldwide proliferation of the Internet, increasing amounts of information are becoming available online in languages that have not received much attention from the IR/NLP community and for which language resources are scarce. For this available information to be useful, it has to be indexed and made searchable by an IR system. Stemming is one of the basic steps in the indexing process. In this paper, we have proposed a stemming algorithm that is corpus-based, and does not rely on linguistic expertise. Retrieval experiments on English, French and Bengali datasets show that the proposed approach is effective for languages that are primarily suffixing in nature. More specifically, we conclude that (i) stemming improves recall for Indian languages like Bengali; and (ii) the performance of a stemmer generated by clustering a lexicon without any linguistic input is comparable to that obtained using standard, rule-based stemmers such as Porter's. Our experiments have, however, raised some issues that need further investigation in future work.

Using a corpus sample for stemmer generation. The clustering step is computationally the most expensive step in our approach. One way to cut down on the amount of time needed for this step would be to use a smaller lexicon, constructed from a sub-sample of a given corpus. As the sample size decreases, the possibility of covering most morphological variants will also decrease. Naturally, this would result in a stemmer with poorer coverage. The nature of the corpus from which the lexicon is generated also determines the coverage of the final stemmer. A corpus that includes documents besides news articles may enrich the lexicon. In future work, we intend to study the effect of corpus size and nature on building language independent stemmers.

Handling excessive conflation. For the Bengali lexicon, we have observed a few instances where two semantically different terms fall in the same cluster due to their string similarity. For example, *Akram* (the name of a cricketer from Pakistan) and *akraman* (to attack) fall in the same cluster, as they share a significant prefix. This problem cannot be addressed by tuning the clustering threshold, since a threshold that separates these strings would also separate pairs such as *akramankarider* (the attackers') and *akraman*, which rightfully belong to a single cluster.

To handle such cases in Bengali, the following strategy may help. Clusters containing two or more roots and their morphological variants are generally bigger than average. We could build a TRIE from the strings in these clusters, and check the fan-outs at each node. If the fan out exceeds a certain limit at a particular node, we may hypothesize that the word formed by the alphabet sequence from the root to that node forms a separate root word. Figure 8 shows how this approach would work for the particular example cited above. Further experimentation, using a much larger set of real-life queries, is needed to estimate the seriousness of this problem, and the effectiveness of the trie-based approach outlined above.

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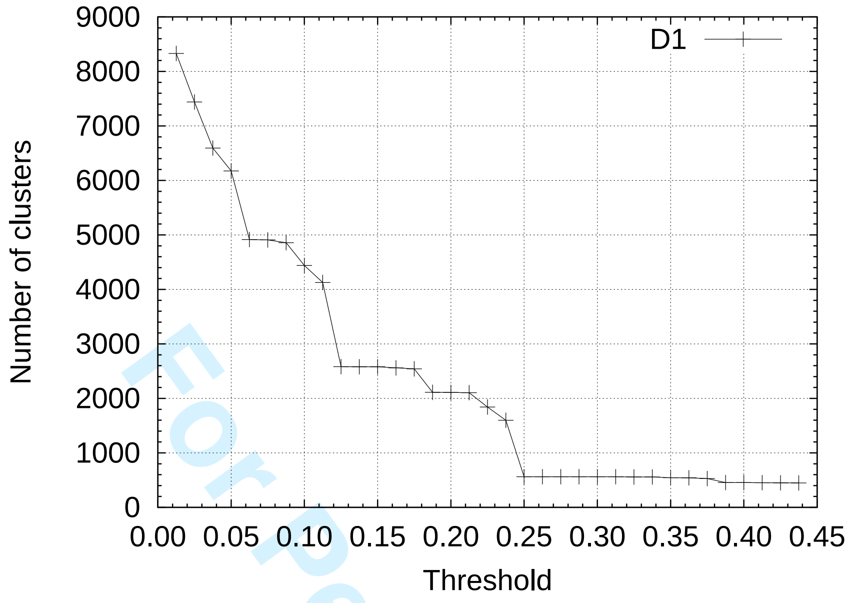


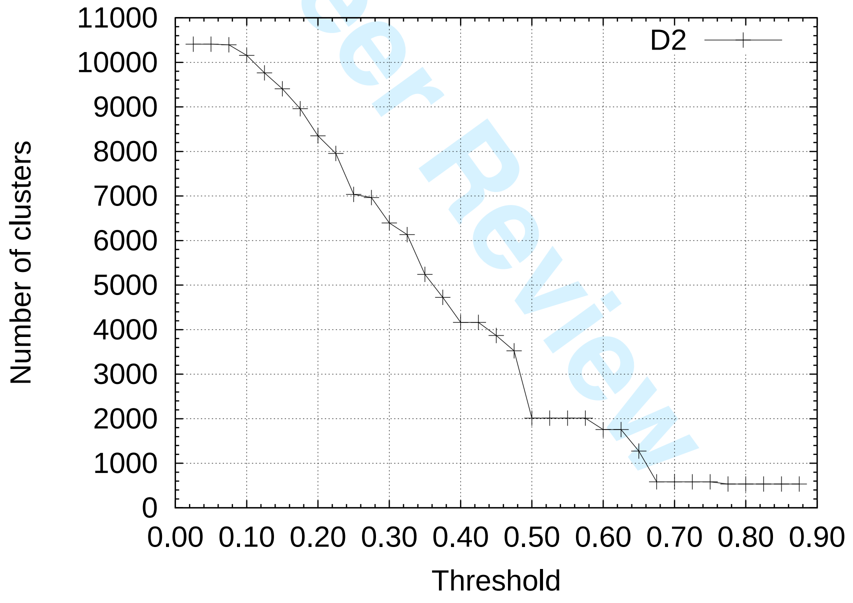
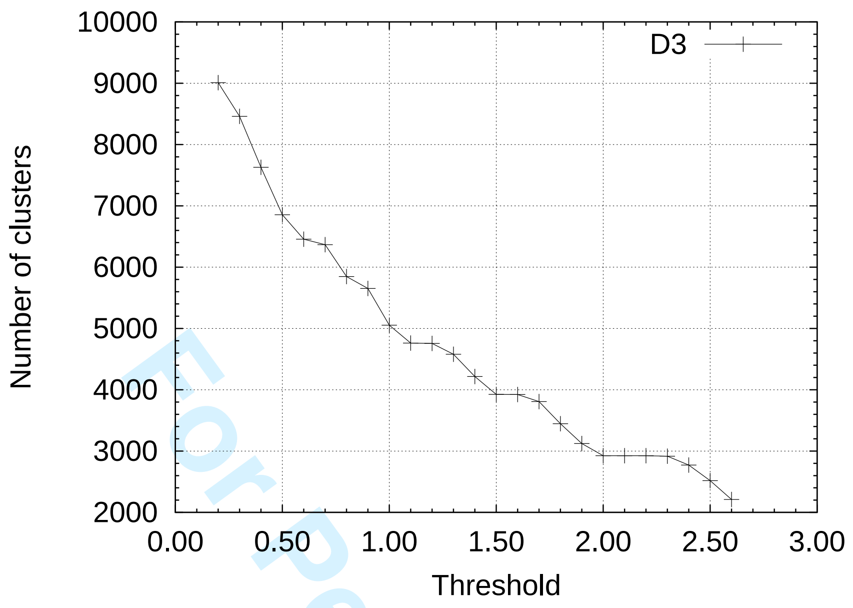


Figure 2: Variation of number of clusters with edge weight thresholds for D_1 and D_2 on WSJ



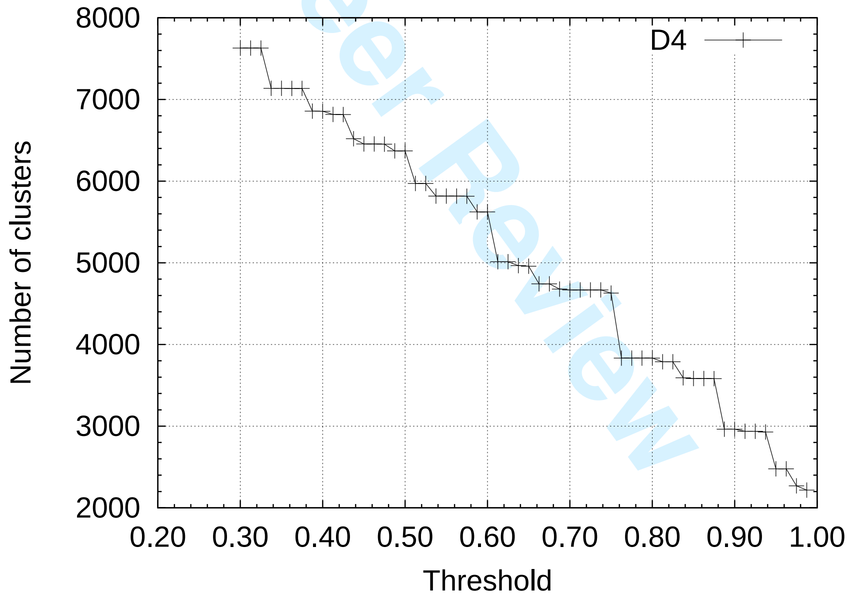


Figure 3: Variation of number of clusters with edge weight thresholds for D_3 and D_4 on WSJ

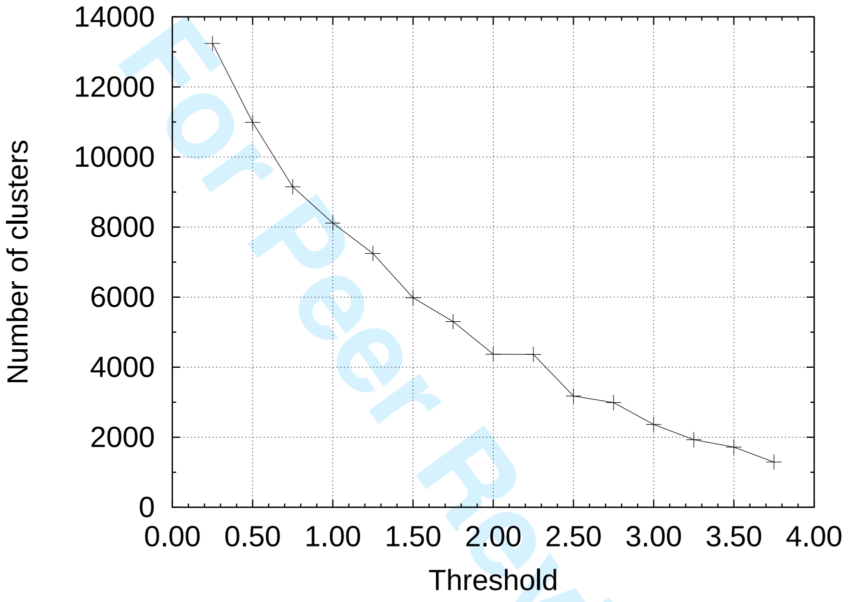


Figure 4: Number-of-clusters vs. threshold curve for AP

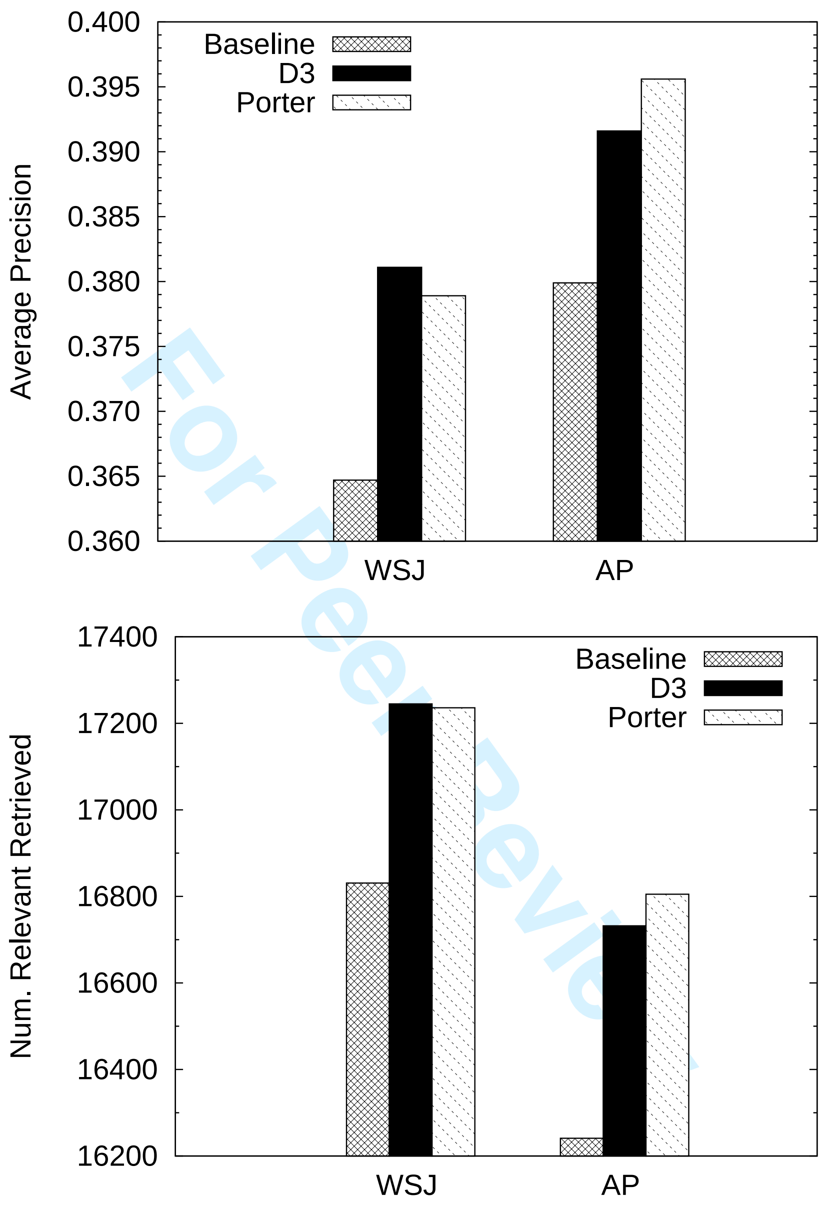


Figure 5: Performance of Various Stemming Strategies for English

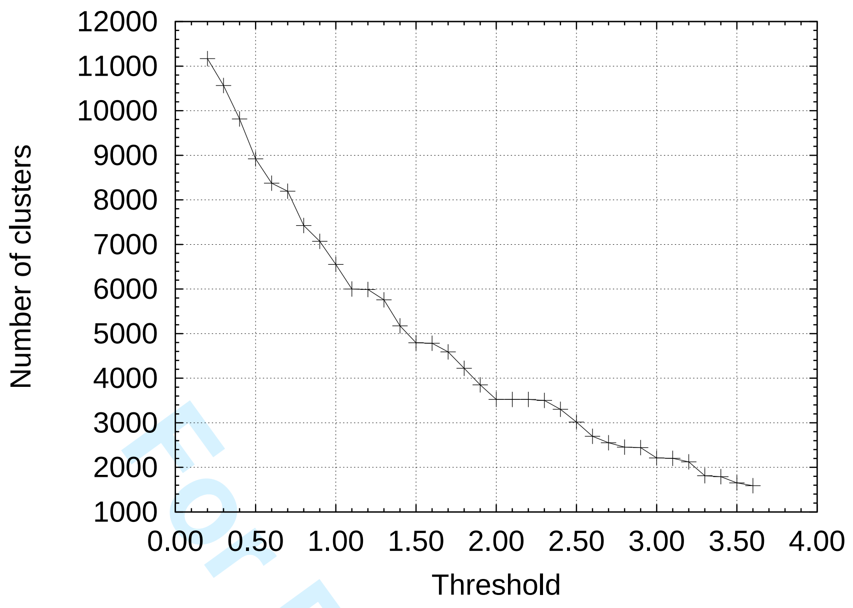


Figure 6: Number-of-clusters vs. threshold curve for the LeMonde Corpus

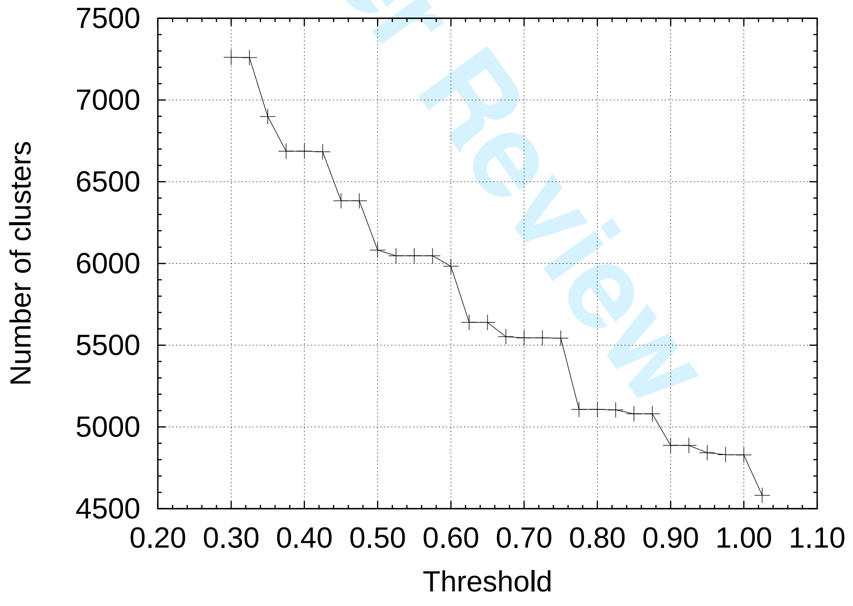


Figure 7: Number-of-clusters vs. threshold curve for the ABP corpus

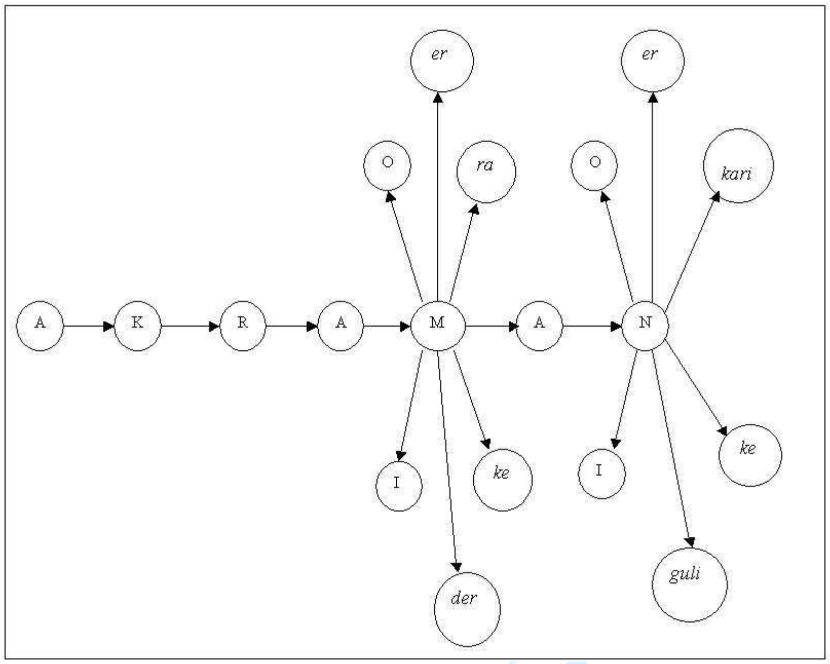


Figure 8: Trie Structure Implemented on a Cluster