

Justsystem-Clairvoyance CLIR Experiments at NTCIR-4 Workshop

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Abstract

At the NTCIR-4 workshop, Justsystem Corporation and Clairvoyance Corporation collaborated in participating in the Cross-Language Retrieval Task (CLIR). We submitted results to the sub-tracks of SLIR and BLIR. For the SLIR track, we submitted Chinese, English, and Japanese monolingual runs. For the BLIR track, we submitted Japanese-English and Chinese-English runs. The major goal of our participation is to evaluate performance and robustness of our recently developed commercial-grade CLIR systems for English, Japanese, and Chinese.

Keywords: *Cross-lingual information retrieval; Evaluation; Retrieval experiments*

1. Introduction

At the NTCIR-4 workshop, Justsystem Corporation (JSC) in Japan and Clairvoyance Corporation (CC) in the USA collaborated in participating in the Cross-Language Retrieval Task (CLIR). A major goal of our participation is to evaluate performance and robustness of our recently developed commercial-grade CLIR systems for English, Japanese, and Chinese. We compared three systems under development or upgrade. The CLIR track has four sub-tracks: single language IR (SLIR), bilingual CLIR (BLIR), bilingual IR via pivot languages (PLIR), and multilingual CLIR (MLIR). We submitted results to the sub-tracks of SLIR and BLIR. For the SLIR track, we submitted Chinese, English, and Japanese monolingual runs. For the BLIR track, we submitted Japanese-English and Chinese-English runs. For each language pair, we submitted two runs based on the *title* (denoted by T) field, two runs based on the *desc* (D) field, and one run based on the *desc* and *narrative* (DN) field. For all the

runs, we report the average precisions and overall recalls using the set of *rigid* relevant documents.

2. System Description

Justsystem Corporation and Clairvoyance Corporation share a common system framework for information retrieval and management, which serves as the foundation of the commercial CLARIT APIs from Clairvoyance for the English language [1] and the commercial ConceptBase product in Japan for the English, Japanese, and Chinese languages. Major functionalities include natural language processing, ad-hoc retrieval, feedback, visualization, etc. Recently, we have added cross-language text retrieval (CLIR) capability into the framework. Both the monolingual systems and the CLIR systems are highly parameterized to allow for system experimentation and optimization.

In an effort to test the performance of all of our available text retrieval tools, we used two different indexing systems and three different retrieval systems in these experiments. CLARIT, a commercial information management toolkit developed at Clairvoyance, served as the indexing and retrieval system for two English runs. ConceptBase Java (CBJ), a commercial text retrieval system developed at Justsystem, served as the indexing system for all the Japanese and Chinese runs, as well as the remaining English runs. In addition, we tested a research text retrieval toolkit called CLJ that runs on top of either the CLARIT or the CBJ indexing engine, and serves as a development environment for our latest research text retrieval algorithms. At NTCIR-4, all CLJ runs are based on the CBJ indexing engine. These three different systems are referred to as CLARIT, CBJ, and CLJ in the remainder of this report.

We have experimented with different features of the monolingual and cross-language systems to identify the significant contributors to an effective

IR system. In the following, we first present components and features shared by both the monolingual and bilingual retrieval system: indexing, retrieval, pseudo relevance feedback, and multi-word term downweighting. Then we present features related to bilingual retrieval: query translation disambiguation.

2.1 Indexing and Retrieval

Both CLARIT and CBJ use NLP for tokenization, storing individual words, full noun phrases, and attested sub-phrases as index terms. An attested sub-phrase is a constituent of a longer noun phrase that also appears independently as a full noun phrase elsewhere in the document collection. CLARIT uses a lexicon-based tokenizer and finite state machine based grammar for English processing. CBJ uses a statistical part-of-speech tagger for tokenization and finite state machine based grammar for processing English, Japanese and Chinese. Indexing involves statistical analysis of a text corpus and construction of an inverted index, with each index entry specifying the index word and a list of texts. Both systems allow the index to be built upon full documents or variable-length subdocuments. We used subdocuments as the basis for indexing and document scoring in our experiments. Sub-documents range in size from 8 to 20 sentences and average about 12 sentences in length.

Retrieval is based on the vector space retrieval model. Various similarity measures are supported in the model. For CBJ and CLARIT in NTCIR-4, we used the dot product function for computing similarities between a query and a document:

$$sim(Q, D) = \sum_{t \in Q \cap D} W_Q(t) \cdot W_D(t) \quad (1)$$

where $W_Q(t)$ is the weight associated with the query term t and $W_D(t)$ is the weight associated with the term t in the document D . The two weights were computed as follows:

$$W_D(t) = TF_D(t) \cdot IDF(t) \quad (2)$$

$$W_Q(t) = C(t) \cdot TF_Q(t) \cdot IDF(t) \quad (3)$$

where IDF and TF are standard inverse document frequency and term frequency statistics, respectively. $IDF(t)$ was computed with the target corpus for retrieval. The coefficient $C(t)$ is an ‘‘importance coefficient’’, which can be modified either manually by the user or automatically by the system (e.g., updated during feedback).

CLJ uses the same inner produce of the query term weights $W_Q(t)$ and the document term weights $W_D(t)$ as shown in formula (1) to compute the similarity score between query Q and document D . The query term weights are

computed with formula (3) again with the coefficient $C(t)$ for assigning differential weights to terms.

The document term weights are standard BM25 [7], as shown in formula (4), in which k_1 is the term frequency smoothing parameter, b is the document length smoothing parameter, d is the document length, and Δ is the average document length in the collection.

$$W_D(t) = \frac{(k_1 + 1) * TF_D(t)}{k_1[(1 - b) + b * (d / \Delta)] + TF_D(t)} \quad (4)$$

Fujita (1999) observed that down weighting of phrasal terms helped with retrieval performance for the NTCIR-1 tasks [2]. We confirmed this observation in our training experiments with NTCIR-3 data [5]. We applied down weighting phrasal terms in all three retrieval systems with the use of the coefficient $C(t)$. For NTCIR-4, we applied a weight of 1.0 to all words and 0.1 or 0.2 to all multi-word phrases.

2.2 Query Expansion

Query expansion through (pseudo) relevance feedback has proved to be effective for improving IR performance. We used pseudo relevance feedback for augmenting the queries. After retrieving some documents for a given topic from the target corpus, we took a set of top ranked documents, regarding them as relevant documents to the query, and extracted terms from these documents. We use two formulae – Prob2 and Rocchio – for extracting and ranking terms for expansion.

$$Prob2(t) = \log(R_i + 1) \times \left(\log\left(\frac{N - R + 2}{N_i - R_i + 1} - 1\right) - \log\left(\frac{R + 1}{R} - 1\right) \right) \quad (5)$$

where N is the number of sub-documents in the reference corpus, N_i is the number of sub-documents that contain the term t in the corpus, R is the number of sub-documents in the top n documents, and R_i is the number of sub-documents that contain the term t in the top n documents. The k terms with the highest score according to this measure are selected and merged with original query to create the final expanded query.

Another formula for extracting terms is the standard Rocchio formula to rank terms in a given set of documents. More precisely, we used term distribution statistics (IDF) from a reference corpus to provide a TF-IDF weighting of terms in the documents and then applied the Rocchio formula to compute the centroid vector for the given set of documents. The coordinates of the centroid vector are taken as term weights and used to rank and select terms:

$$Rocchio(t) = IDF(t) \cdot \frac{\sum_{D \in DocSet} TF_D(t)}{NumDoc} \quad (6)$$

where $IDF(t)$ is the Inverse Document Frequency of term t in reference database, $NumDoc$ the number of documents in the given set of documents, and $TF_D(t)$ the term frequency score for term t in document D .

Once terms for expansion were extracted and ranked, they were combined with the original terms in a query to form an expanded query.

$$Q_{new} = k \times Q_{orig} + Q_{exp} \quad (7)$$

in which Q_{new} , Q_{orig} , Q_{exp} stand for the new expanded query, the original query, and terms extracted for expansion, respectively. Weighting options for Q_{exp} include:

- Uniform: all expansion terms takes the same weight (e.g., $W(t) = 1$)
- Normalized: the expansion terms take the Rocchio or Prob2 scores normalized by their appropriate max scores, e.g., with the Rocchio formula,

$$W(t) = \frac{W_{Rocchio}(t)}{\max(W_{Rocchio}(t))} \quad (8)$$

- Scaled: both Q_{orig} and Q_{exp} are normalized with the sum of the term scores. For Q_{orig} , the original weights are used. For Q_{exp} , the Rocchio or Prob2 scores are used. E.g., with the Prob2 formula,

$$W(t) = \frac{W_{Prob2}(t)}{\sum W_{Prob2}(t)} \quad (9)$$

The following is a complete description of the term scoring and expansion steps using CLJ as an example:

- Retrieve the top **10** documents using the original query Q_{orig} and weight function **BM25(k₁=1.2, b=0.2)** and phrase weight = **0.1**
- Select the top **35** terms based on the Prob2 formula after throwing out all terms with frequency one in the top 10 documents to create Q_{exp} . The original query terms are included in the selection process.
- Merge the queries as follows: $Q_{new} = 0.25 \times Q_{orig} + Q_{exp}$ [Note that Q_{orig} and Q_{exp} are normalized so that their weights sum to 1.0 prior to merging.]
- Retrieve the final document set using Q_{new} and weight function **BM25(k₁=1.2, b=0.3)** and phrase weight = **0.2**

For CLJ, all parameters were optimized on the NTCIR-3 query set for the three languages as a whole. We did not try to optimize on each language independently to reduce overfitting. In practice, we have found the optimal parameters to be very similar for all languages. For CBJ and CLARIT, we optimized on the NTCIR-3 query sets for individual language pairs. The settings will be reported in sections with the corresponding evaluation runs.

3. CLIR Retrieval Track

We have participated in two sub-tracks of the CLIR track: single language IR (SLIR) and bilingual IR (BLIR). For details on the CLIR track and its sub-tracks, the topic sets, the document collections, and evaluation of the tracks, the reader is referred to the overview of the CLIR track [4]. For SLIR, we submitted runs for Japanese, English, and Chinese monolingual retrieval. For BLIR, we submitted runs for Japanese-English and Chinese-English retrieval. We report the results of these runs based on evaluation against “rigid” relevant documents.

3.1 Single Language IR track

This section describes the parameters used for the monolingual runs at NTCIR-4.

3.1.1 Japanese Retrieval

For Japanese retrieval, we used CBJ to process the documents and topics. The Japanese documents were first parsed into linguistically meaningful units: NPs, Adj, Adv, and Verbs, which were used as indexing terms for building Japanese monolingual database. Surface variants were normalized to their root forms. A stop word list of was used to filter out general stop words and query-dependent words such as 記述 and 内容. Japanese topics were parsed similarly.

For Japanese retrieval, we compared CBJ and CLJ. CBJ used formulae (2) and (3) term weighting and the Rocchio method was used for extracting terms. We used the top 30 terms from the top 30 documents for query expansion. Formula (8) was used for feedback term weighting. The CLJ system used Prob2 for extracting query expansion terms, and formula (9) for merging expansion terms with the original query terms.

The official results from NTCIR-4 were presented in Table 1. CLJ outperformed CBJ overall.

From the description of the term weighting algorithms in section 2.2, we see that CLJ has a lot of parameters. This is not a serious drawback as long as an appropriate set of default parameters is available and the system is relatively robust to minor changes in the parameter settings. In order to measure the robustness of the system, we performed a sensitivity analysis on the monolingual

Japanese title run from CLJ, based on the rigid relevance judgments. For each of the system components, we compute average precision over a range of parameter values. To conserve space, we report only the total range of results, rather than the complete performance table. The first row of Table 2 shows the pre-expansion performance. All other results are computed after query expansion.

Run	Feature	Avg prec	Recall
J-J-T-cbj	Rocchio Formula (8)	0.2686	4487/7137
J-J-T-clj	Prob2 Formula (9)	0.389	5868/7137
J-J-D-cbj	Rocchio Formula (8)	0.2622	4417/7137
J-J-D-clj	Prob2 Formula (9)	0.3747	5684/7137

Table 1: Japanese Retrieval, rigid

We can see that performance varies by no more than about 10% for each set of parameters, indicating that the system is relatively stable (Table 2). Even more encouraging, we find that optimizing over the NTCIR-3 collection was extremely effective, putting us at or near the top of the range in every case. The only way we could have improved our performance would have been to expand with 30 terms instead of 35, giving us a meager gain of 0.002.

Parameters	Submission	Range
BM25 (k_1 , b)	0.311	0.306-0.311
Phrase weight (0.0-1.0)	0.389	0.361-0.389
# docs (5-20) # terms (20-40)	0.389	0.361-0.391
Query weight (0.0-1.0)	0.389	0.366-0.389

Table 2: Japanese Retrieval Parameter Calibration, Rigid

3.1.2 English Retrieval

For English retrieval, we compared CLARIT and CLJ, with CLJ taking the index from CBJ. First, the English documents were parsed into linguistically meaningful units: NPs, Adj, Adv, and Verbs. Only NPs were used as indexing terms for building English monolingual database. Surface variants were normalized to their root forms. A stop word list of 115 words was used to filter out general stop words and query-dependent words such as “information” or “document”. English topics were parsed similarly. Clarit used formulae (2) and (3) term weighting and the Rocchio method was used for extracting terms. We used the top 30 terms from the top 20 documents for query expansion. Formula (8) was used for feedback term weighting. The CLJ system used Prob2 for extracting query expansion terms, and formula (9)

for merging expansion terms with the original query terms.

The official results from NTCIR-4 were presented in Table 3. The CLJ based runs performed overall better compared with the CLARIT based runs.

run	feature	Avg prec	Recall
E-E-T-clarit	Rocchio Formula (8)	0.3145	4403/5866
E-E-T-clj	Prob2 Formula (9)	0.3412	4259/5866
E-E-D-clarit	Rocchio Formula (8)	0.307	4380/5866
E-E-D-clj	Prob2 Formula (9)	0.3382	4500/5866

Table 3: English Retrieval, Rigid

3.1.3 Chinese Retrieval

For Chinese retrieval, we compared CBJ and CLJ. The Chinese documents were first parsed by the Chinese NLP module in CBJ into linguistically meaningful units: NPs, Adj, Adv, and Verbs. NPs were used as indexing terms for building Chinese monolingual database. Surface variants were normalized to their root forms. A stop word list of 170 words was used to filter out general stop words and query-dependent words such as 内容 and 文件. The part-of-speech tagger in CBJ was originally developed for simplified Chinese. We conducted character-based substitution between simplified Chinese characters and traditional Chinese characters to make the module process traditional Chinese characters. The simple conversion was prone to error because of the ambiguity in converting traditional Chinese characters to simplified Chinese characters.

run	feature	Avg prec	Recall
C-C-T-cbj	Rocchio Formula (8)	0.1327	874/1318
C-C-T-clj	Prob2 Formula (9)	0.1899	1017/1318
C-C-D-cbj	Rocchio Formula (8)	0.1384	809/1318
C-C-D-clj	Prob2 Formula (9)	0.1886	1062/1318

Table 4: Chinese Retrieval, Rigid

In CBJ runs, we used $tf*idf$ score for term weighting and the Rocchio method for query expansion. We used the top 30 terms from the top 20 documents for query expansion. In CLJ runs, Prob2 was used for extracting expansion terms, and scaled term weighting was used for merging feedback terms with the original query terms.

The official results from NTCIR-4 were presented in Table 4. Again, CLJ based runs had higher scores than the CBJ based runs. However, the results of all our runs were low compared with those of many groups in the NTCIR-4 submission. Preliminary analysis suggests that missing lexical terms in the parsing dictionary and wrong

conversion between simplified Chinese and traditional Chinese are the main causes for extracting wrong terms from the topics for indexing and retrieval.

For example, in topic 22 (合法經營, 起亞汽車, 意見) the word "起亞 (Kia)" is not registered in the CBJ traditional Chinese dictionary used for tokenization. Consequently, it was interpreted as verb "起 (rise, occur)" and noun "亞 (Asia)". Another example of missing lexical entries is topic 39 (外勞, 驅逐, 人權), in which "外勞 (foreign worker)" is parsed as person name "外" and verb "勞(work)". As a result, the system had low score for these topics.

In topic 26 (中國, 反應, 台灣, 外交關係), the CBJ traditional Chinese dictionary has "關係", but doesn't have the correct word "關係". "關係 (relation)" was parsed as noun "關 (checkpoint, custom)" and unknown word "係". This is due to the error in character convert between Simplified Chinese and Traditional Chinese characters.

The above errors suggest that we need to develop a better conversion algorithm between simplified Chinese characters and traditional Chinese characters, and that lexicon-free approaches, such as n-gram based indexing should be incorporated into the indexing and retrieval processes.

3.2 Bilingual CLIR track

For bilingual CLIR, we adopted query translation as the means for bridging the language gap between the query language and the document language. We have experimented with Japanese-English retrieval and Chinese-English retrieval. For Japanese-English retrieval, first, the Japanese topics were parsed into words and phrases with Japanese NLP module in CBJ. Then the terms were translated into English. For Chinese-English retrieval, we used a part-of-speech tagger to get the terms, without phrase construction, and then translate the Chinese terms into English.

For both types of runs, the English document collection was indexed as described in section 3.1.2. Once queries were translated from the source language to the target language English, English documents were retrieved the same way as in English monolingual retrieval as described in section 3.1.2.

3.2.1 Japanese-English Retrieval

The Japanese-English translation lexicon was a combination of several lexicons: the EDR Japanese-English bilingual dictionary¹, the EDCIT and ENAMDUCT dictionaries², a commercial lexicon Atok from developed by Justsystem³, a lexicon extracted from the Yomiuri parallel corpus

[9] via a translation pair extraction tool, and a list of famous Chinese person names collected from the internet.

We compared CBJ and CLJ for Japanese-English retrieval. In addition to a very comprehensive translation lexicon and language independent features such as pseudo relevance feedback, CBJ employs CLIR specific techniques for choosing the best translation during the translation process. To disambiguate multiple translations of a query term, CBJ used the Daily Yomiuri corpus [9], a Japanese-English sentence aligned corpus, to validate the correspondences of the translation pairs in aligned Japanese-English sentences. Syn operators were used when multiple translations were kept for a source term [6]. Once translations were selected, the Rocchio method was used for extracting feedback terms, taking to 20 terms from the top 20 subdocuments for post-translation query expansion. Feedback terms were merged with original query terms based on formula (8).

Run	feature	Avg prec	Recall
J-E-T-cbj	Rocchio Formula (8)	0.2131	3688/5866
J-E-T-clj	Prob2 Formula (9)	0.2125	2965/5866
J-E-D-cbj	Rocchio Formula (8)	0.262	3885/5866
J-E-D-clj	Prob2 Formula (9)	0.2427	3733/5866

Table 5: Japanese-English Retrieval, Rigid

For CLJ runs, we took the translated expanded query from CBJ and conducted another round of query expansion. Here, Prob2 was used for extracting feedback terms, which were then merged with the CBJ-query terms based on formula (9).

Table 5 shows the results with both systems for title and description queries. The results show that with additional round of feedback on top of CBJ output, CLJ was not able to improve the retrieval performance further.

3.2.2 Chinese-English Retrieval

The Chinese-English translation lexicon was based on CEDICT version 3⁴, which has a total of more than 51,400 entries, expanded with a lexicon of technical terms of about 1400 entries collected from the internet, and a list of names of about 1000 famous person names. The list of famous persons was constructed by converting the famous person name lexicon in the Japanese-English lexicons described in the previous section. We call this lexicon expanded CEDICT or expCEDICT. For the Chinese-English retrieval task, we further expanded the expCEDICT lexicon by adding translations of multi-word term translations. We

¹ <http://www.ijnet.or.jp/edr/E05JEBIL.txt>

² <http://www.csse.monash.edu.au/~jwb/edict.html>

³ www.atok.com

⁴ <http://www ldc.upenn.edu/doc/LDC2002L27/readme.txt>

used CLARIT for English retrieval for all the experiments reported here.

Our approach to translating multi-word terms for Japanese and Chinese is based on previous work for European languages [3]. The method, similar to [8], involves generating possible candidate translations using a bilingual dictionary and then attesting the candidates, ranking them by their frequency in a reference corpus. The steps are as follows:

- Extract all multiword terms using NLP modules from corpus
- Find those terms unknown to CEDICT
- Among those find those terms whose parts are known to CEDICT
- Generate English translation candidates for these phrases by translating their subparts translation candidates in NTCIR-3

With the NTCIR-3 Chinese evaluation corpus, we extracted and validated 236,652 multi-word Chinese terms and their corresponding translations.

We used the Chinese-English retrieval track as a small-scale experiment on the effectiveness of the additional translations of the multi-word terms. For this experiment, we used the Rocchio method for post-translation query expansion, by extracting the top 30 terms from the top 20 documents. Multi-word terms were downweighted to 0.2. We did not use translation disambiguation for choosing the best translations, as we did not have time to adapt our existing disambiguation module to deal with multi-word terms.

Table 6 shows the retrieval results for both the title and description topics. The results showed that by expanding the base lexicon with automatically extracted translations of phrases, retrieval performance can be improved slightly, but the improvement is not significant. Description based runs had lower precision scores than the title based runs. This is probably due to the increasing noise in translation when more terms were translated, which suggests that translation disambiguation should be incorporated into the process.

Run	feature	Avg prec	Recall
C-E-T-1	expCedict	0.1627	3041/5866
C-E-T-2	expCedict MWE	0.166	3378/5866
C-E-D-1	expCEDICT	0.1552	3103/5866
C-E-D-2	expCedict MWE	0.1557	3184/5866

Table 6: Chinese-English Retrieval, Rigid

4. Summary

In NTCIR-4, we conducted monolingual and bilingual experiments to compare three retrieval systems under development at Justsystem

Corporation in Japan and Clairvoyance Corporation in the USA. With the experiments at NTCIR-4, we evaluated the commercial and research versions of our retrieval systems. The CLIR experiments have shown promise for some of the newly developed techniques, such as scaled merging during feedback.

For future work, we need to analyze the differences between the retrieval systems, and evaluate the contribution of the component features.

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