Japanese Probabilistic Information Retrieval Using Location and Category Information

Masaki Murata, Qing Ma, Kiyotaka Uchimoto, Hiromi Ozaku, Masao Utiyama and Hitoshi Isahara
Intelligent Processing Section, Kansai Advanced Research Center, Communications Research Laboratory, Ministry of Posts and Telecommunication
588-2, Iwaoka, Nishi-ku, Kobe, 651-2492, Japan
Phone: +81-78-969-2181 Fax: +81-78-969-2189 E-mail: murata@crl.go.jp
http://www-karc.crl.go.jp/ips/murata

Abstract

Robertson’s 2-poisson information retrieve model does not use location and category information. We constructed a framework using location and category information in a 2-poisson model. We submitted two systems based on this framework to the IREX contest, Japanese language information retrieval contest held in Japan in 1999. For precision in the A-judgement measure they scored 0.4926 and 0.4827, the highest values among the 15 teams and 22 systems that participated in the IREX contest. We describe our systems and the comparative experiments done when various parameters were changed. These experiments confirmed the effectiveness of using location and category information.

Keyword: 2-poisson model, Location information, Category information

1 Introduction

Information retrieval (IR) has become an increasingly important area of research due to the rapid growth of the Internet. In 1999 the Information Retrieval and Extraction Exercise contest (IREX) was held in Japan. We submitted two systems to this contest. Their precision in the A-judgement measure was 0.4926 and 0.4827, the highest values among the 15 teams and 22 systems in the IREX contest. This paper describes our systems and the comparative experiments done when various parameters were changed.

Our information retrieval method uses Robertson’s 2-poisson model, which is one kind of probabilistic approach. But, Robertson’s method does not use location or category information, which should be used to facilitate information retrieval. Against this background, we constructed a framework by using location information, category information, and detailed information in a 2-poisson model. We verified the effectiveness of using these three types of information by doing comparative experiments. When the 2-poisson model is used a term extraction method needs to be selected. In this paper, we describe four term extraction methods, and compared them in experiments.

2 Information retrieval

2.1 Task

The information retrieval tasks in this paper are identical to those for the IREX contest. The database used for information retrieval (the same used in IREX) is from two-years (1994-1995) of a Japanese newspaper. We retrieved from this database documents which satisfied the information condition for a Japanese language query. The following is an example of a query. (The data is from the IREX preliminary experiment.)

Example of a Japanese query

<TOPIC><TOPIC-ID>1001</TOPIC-ID><DESCRIPTION>enterprise amalgamation</DESCRIPTION><NARRATIVE></NARRATIVE></TOPIC>

English translation

<TOPIC><TOPIC-ID>1001</TOPIC-ID><DESCRIPTION>enterprise amalgamation</DESCRIPTION></TOPIC>

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. To copy otherwise, to republish, to post on servers or to redistribute to lists, requires prior specific permission and/or fee.

Proceedings of the 5th International Workshop Information Retrieval with Asian Languages

Copyright ACM 1-58113-300-6/00/09 ... $5.00
The condition for a relevant document is that in the document an announcement of enterprise amalgamation materialization is described and the name of the enterprise which participated the amalgamation can be recognized. Also, one of the field of amalgamation enterprise and its purpose should be able to recognized. Enterprise amalgamation contains enterprise annexation, enterprise integration, and enterprise purchasing.

Example of a Japanese document

In this document, the newspaper information category (the economic or political pages) is indicated by the term "category" (the economic or political pages) is indicated by the term "category". Robertson's method calculates each document’s score using the following equation

\[
Score(d,q) = \frac{tf(d,t)}{tf(d,t) + \frac{length(d)}{\Delta}} \log N \frac{df(t)}{df(t) + kq} + \frac{K_{category}(d)}{K_{category}(d) + K_{location}(d,t) + length(d) + \Delta}
\]

where terms occur in a query. \( tf(d,t) \) is the frequency of a term \( t \) in a document \( d \), \( df(t) \) is the frequency of \( t \) in a query, \( length(d) \) is the length of a document \( d \), and \( \Delta \) is the average length of the documents. \( k_1 \) and \( k_q \) are constants which are set by experiments.

In this equation, we call \( T F(d,t) \) the TF term, \( IDF(t) \) the IDF term, \( T F_q(q,t) \) the TFQ term, \( T F_p(q,t) \) the TFQ term, \( T F_S(q,t) \) the TFQ term, \( T F_t(q,t) \) the TFQ term, and \( T F_f(q,t) \) the TFQ term.

Our method adds several extended terms to this equation, and is expressed by the following equation.

\[
Score(d,q) = K_{category}(d) \left\{ \sum_{term \ t \ in \ q} (TF(d,t) \times IDF(t)) + \frac{K_{detail}(d,t)}{K_{location}(d,t)} + \frac{length(d)}{length(d) + \Delta} \right\}
\]

The TF, IDF and TFQ terms in this equation are identical to those in Eq. (1). The term \( K_{category} \) has a higher value when a document is longer. This term is made because if the other information is exactly equal, the longer document is more likely to include the content requested by the query. \( K_{category} \), \( K_{detail} \) and \( K_{location} \) are extended numerical terms made to improve precision. \( K_{category} \) uses the category information of the document found in newspapers, such as the economic and political pages. \( K_{location} \) uses the location of the term in the document. If a term is in the title or at the beginning of the body of the document, it is given a higher weighting. \( K_{detail} \) uses the information such as whether the term is a proper noun and or a stop word such as "document" and "thing". In the next section, we explain these extended numerical terms in detail.

2.3 Extended numerical terms

We use the three extended numerical terms of \( K_{location} \), \( K_{category} \), and \( K_{detail} \) as in Eq. (2). This section explains them in detail.

1. Location information (\( K_{location} \))

In general, the title or the first sentence of the body of a document in a newspaper very often indicates its subject. Therefore, the precision of information

\[\text{BM25}\]
retrieval can be improved by weighting the terms in these two locations. The term $K_{location}$ performs this task, and changes the weight of a term based its location at the beginning of the document. If a term is in the title or at the beginning of the body, it is given a high weighting. Otherwise, it is given low weighting. This term is expressed as follows:

$$K_{location}(d, t) = \begin{cases} k_{location,1} & \text{(when a term } t \text{ occurs in the title of a document } d), \\ 1 + k_{location,2} \frac{(\text{length}(d) - 2 \ast P(d, t))}{\text{length}(d)} & \text{(otherwise)} \end{cases} \quad (3)$$

$P(d, t)$ is the location where a term $t$ occurs in the document $d$. When a term occurs more than once in a document, its first occurrence is used. $k_{location,1}$ and $k_{location,2}$ are constants which are set by experiments.

2. Category information ($K_{category}$)

$K_{category}$ uses category information such as the economic and political pages. This functions as a technique called relevance feedback [10]. First, we specify the categories which occur in the top 100 documents of the first retrieval when $K_{category} = 1$. Then, we increase the scores of documents having the same categories. For example, if economic pages often occur in the top 100 documents of the first retrieval, we increase the score of a document whose page is an economic page and decrease the score of the document whose page is different. $K_{category}$ is expressed as follows:

$$K_{category}(d) = 1 + k_{category} \frac{\text{RatioA}(d) - \text{RatioB}(d)}{\text{RatioA}(d) + \text{RatioB}(d)} \quad (4)$$

where $\text{RatioA}$ is the ratio of a category in the top 100 documents of the first retrieval. $\text{RatioB}$ is the ratio of a category in all the documents. The value of $K_{category}(d)$ is large, when $\text{RatioA}$ is large (page of a document $d$ occurs frequently in the top 100 documents of the first retrieval.) and $\text{RatioB}$ is small (page of a document $d$ does not occur often in all the documents.). $k_{category}$ is a constant which is set by experiments.

3. Other information ($K_{detail}$)

$K_{detail}$ is a more detailed numerical term that uses different information, such as whether the term is a proper noun and whether the term is a stop word such as “document” and “thing”. If a term is a proper noun, it is weighted high. If a term is a stop word, such as “document” and “thing,” it is weighted low. $K_{detail}$ is expressed as follows for simplicity, the variables for a document and a term, $d$ and $t$, are omitted:

$$K_{detail} = k_{descr} k_{proper} k_{nado} k_{num} k_{hira} k_{neg} k_{stopword} \quad (5)$$

Each term in this equation is explained below.

- $K_{descr}$
  When a term is obtained from the title of a query, i.e. DESCRIPTION, $K_{descr} = k_{descr}(> 1)$. Otherwise, $K_{descr} = 1$. This is because a term obtained from the title of a query is important.

- $K_{proper}$
  When a term is a proper noun, $K_{proper} = k_{proper}(> 1)$. Otherwise $K_{proper} = 1$. This is because a term that is a proper noun is important.

- $K_{nado}$
  When a term is followed by the Japanese word $nado$ (such as) in a query sentence, $K_{nado} = k_{nado}(> 1)$. Otherwise $K_{nado} = 1$. A term which is followed by the Japanese word $nado$ is specific in meaning and is just as important as a proper noun.

- $K_{num}$
  When a term is numeric, $K_{num} = k_{num}(< 1)$. Otherwise, $K_{num} = 1$. A term which consists of only numerals does not contain much relevant information making it unimportant to a query.

- $K_{hira}$
  When a term consists of hiragana characters only, $K_{hira} = k_{hira}(< 1)$. Otherwise, $K_{hira} = 1$. A term which consists of only hiragana characters does not contain much relevant information making it unimportant to a query.

- $K_{neg}$
  When a term is obtained from a region tagged with a NEG tag in a query, $K_{neg} = k_{neg}$. Otherwise $K_{neg} = 1$.

In a query of the IREX contest, an expression, “... wa nozoku” (... is excepted), as in the following query, was tagged with a NEG tag.

**Example Japanese query**

<TOPIC>
<TOPIC-ID>1003</TOPIC-ID>
<DESCRIPTION>
<NARRATIVE></NEG></NARRATIVE>
</TOPIC>

**English translation**

<TOPIC>
<TOPIC-ID>1003</TOPIC-ID>
<DESCRIPTION>Dispatch of the United Nations forces</DESCRIPTION>
<NARRATIVE>Dispatch of the United Nations forces in the activity of UN such as peace maintenance activity is described. The purpose of the dispatch or the target region should be described. <NEG>A document describing the discussion of whether the Self-Defense Forces of Japan is dispatched to UN or not is elimanted.</NEG></NARRATIVE>
</TOPIC>

If a term from a region tagged with a NEG tag is used, non-relevant documents are often retrieved and therefore such a term is weighted
low. In this paper, $k_{neg}$ is set to 0. This indicates that a term from a region tagged with a NEG tag is not used in retrieval.

- $K_{stopword}$
  - When a term is a stopword such as jouken (condition), kiji (document) and bai (case), $K_{stopword} = k_{stopword} < 1$. Otherwise $K_{stopword} = 1$. A term that is a stopword is unimportant.

Each constant, such as $k_{descr}$, is set experimentally.

### 2.4 How to extract terms

Before being able to use Eq. (2) in information retrieval, we must extract the terms from a query. This section describes how to do this. With regard to term extraction, we considered the several methods listed below.

1. Method using only the shortest terms
   - This is the simplest method. The method divides the query sentence into short terms by using the morphological analyzer “juman” and eliminates non-nominal words and stop words. The remaining words are used in the retrieval process.

2. Method using all term patterns
   - In the first method the terms are too short. For example, “enterprise” and “amalgamation” are used instead of “enterprise amalgamation.” We thought that we should use “enterprise amalgamation” in addition to the two short terms. Therefore, we decided to use both short and long terms. We call this “all-term patterns method.” For example, when “enterprise amalgamation materialization” was inputted, we use “enterprise”, “amalgamation”, “materialization”, “enterprise amalgamation”, “amalgamation materialization”, and “enterprise amalgamation materialization” as terms for information retrieval. We thought that this method would be effective because it uses all term patterns. But, we also thought that it is inequitable that only the three terms of “enterprise,” “amalgamation,” “materialization,” are derived from “... enterprise ... amalgamation ... materialization ...”, while on the other hand six terms are derived from “enterprise amalgamation materialization.” We examined several normalization methods in preliminary experiments, and decided to divide the weight of each term by $\sqrt{n(n+1)/2}$, where n is the number of successive words. For example, in the case of “enterprise amalgamation materialization”, n = 3.

3. Method using a lattice
   - Although the method using all-term patterns is effective for use with all patterns of terms, it needs to be normalized by using the adhoc equation $\sqrt{n(n+1)}$. Thus, we considered the method where all the term patterns are stored into a lattice structure. We use the patterns in the path where the score in Eq. is the highest. (This method is almost same as Ozawa’s [5]. The differences are the fundamental equation for information retrieval, and whether to use or not use a morphological analyzer.)

4. Method using down-weighting [6]
   - This is the method that Fujita proposed at the IREX contest, and we examined after the contest. It is similar to the all-term patterns method. It uses all the term patterns but the normalization is different from the all-term patterns method. It does not change the weight of the shortest terms; and decreases the weight of the longer terms. We decided to multiply the weight $k_{down} = 1$ to a term, when it consisted of x short terms, where $k_{down}$ was set by experiments. This method basically uses the shortest terms while also using the longer terms by down-weighting them.

### 3 IREX contest results

For our two submissions to the IREX contest, we selected the “all-term patterns” and “lattice structure” methods to extract terms [7] and set the constants of the extended terms in order to maximize the precision in the preliminary-run data as follows.

1. System A
   - It used the lattice method for the term extraction. The parameters were set as follows; $k_{location1} = 1.35$, $k_{location2} = 0.125$, $k_{category} = 0$, $k_{descr} = 1.5$, $k_{proper} = 2$, $k_{rado} = 1$, $k_{num} = 0.5$, $k_{hirg} = 0.5$, $k_{neg} = 0$, $k_{stopword1} = 0$, $k_{stopword2} = 0.5$, $k_{q} = 1$, and $k_{q} = 0.1$. Terms obtained from DESCRIPTION are handled as terms different from terms obtained from NARRATIVE.

2. System B
   - IREX allowed two systems to be submitted.

---

8 Since, Japanese is an agglutinative languages like Chinese, there are no spaces between words and a morphological analyzer is necessary to divide a sentence into words.

9 Although this paper deals only with Japanese, not English, for this explanation we use English examples for the English readers. This method handles compound nouns and can be used not only for Japanese but also for English.
It used all-term patterns method for term extraction. The parameters were set as follows; $k_{location} = 1.3, k_{category} = 0.15, k_{decr} = 1.75, k_{prop} = 2, k_{nodo} = 1.7, k_{num} = 0.5, k_{hira} = 0.5, k_{stopword,1} = 0, k_{stopword,2} = 0.5, k_{1} = 1$, and $k_{0} = 0$. Terms obtained from DESCRIPTION were handled as the terms different from those obtained from NARRATIVE.

In the contest, the results for the 22 systems were submitted by the 15 teams. Their R-Precisions are shown in Table 1. The first column of the table indicates the names of the systems. Our two systems, System A and System B correspond to 1135a and 1135b. A-Judgment and B-Judgment are the evaluation criteria determined by the IREX committee. A-Judgment means that a document whose topic is relevant to a query is judged as a relevant document. B-Judgment means that a document whose topic is partly relevant to a query is also judged as a relevant document. Although our systems were not the highest in B-Judgment, they were the highest among all the systems in A-Judgment. This result indicates that our method is relatively superior.

### 4 Experiments

In this section we describe several experiments done to test the effectiveness of the several methods used in our system. In the experimental results of this section, we also show Average Precision (the average of the precision when each relevant document is retrieved) in addition to R-Precision. For the comparison experiments, t-test is used. A method tagged with “#” in Tables 2 to 4 is the base for comparison. A method tagged with “*” is superior to the base method at the significance level of 5%, and a method tagged with “**” is superior at the significance level of 1%. T-test is used only in formal-run experiments. (The preliminary-run data contained six queries, and the formal-run data contained thirteen queries.)

#### 4.1 Comparison of term extraction methods

We showed the following four term extraction methods in Section 2.4:

1. Method using the shortest terms
2. Method using all the term patterns
3. Method using a lattice
4. Method using down-weighting

All the comparison results are shown in Table 2. In Table 2(a) all extended terms were used. In Table 2(b) no extended terms were used. In the down-weighting method we tested the two cases of $k_{down} = 0.1$ and $k_{down} = 0.01$.

The precision of the all-term patterns method was lowest in the formal run. It needed to be normalized using the adhoc equation. Since it had the lowest precision, it was thought to be inferior to the other methods. Also, it was shown by t-test to be significantly inferior to the shortest terms method.

Although the down-weighting method obtained the highest precision when no extended terms were used, it was not as effective when all the extended terms were used. Since it was significantly different from any of the other methods, cannot say that it is very reliable. But, in the case where a small amount of retrieval information was used (i.e. no extended terms) it was very effective.

Since only the shortest terms method is significantly different from the all-term patterns method, we think it is a sound method which can provide reliable results. Since the lattice and the down-weighting methods are not significantly different from the all-term patterns method, we think that they must have some problems. One problem that occurred when using the lattice method was that the terms used in retrieval easily changed depending on the context, while the down-weighting method’s problem was that it uses the extra terms even if it down-weights them. However, it is thought by us that using longer terms in addition, is better than using only the shortest terms. We have to continue the investigation of term extractions.

#### 4.2 Effectiveness of extended terms

Extended terms used in this paper are classified into the following three categories:

1. $K_{location}$ (location information)
2. $K_{category}$ (category information)
3. $K_{detail}$ (detail information)

(Here, $K_{detail}$ contains $K_{length} = \frac{length}{length + x}$ which is the numerical term for a document length in Eq 4.)

In order to verify the effectiveness of the above three extended terms, we carried out eight experiments in which these three terms were alternately used or not used. These experiments were performed using “the lattice method” and “the shortest terms method”. The results are shown in Table 4.

The last line of the table is the case where no extended terms were used and the first line of the table is the case where they were all used. When we compared the two lines, we found there was an improvement of 0.027 to
0.045 when our extended terms were used. (For example, the average precision of A-Judgement of the shortest terms method improved from 0.488 to 0.4935, i.e., 0.0447.) This indicates that the extended terms used in our experiment were totally effective. Retrieval precision can be improved by using location and category information in addition to Robertson’s probabilistic retrieval method.

A method that uses one of the extended terms is more precise than one using no extended terms. Thus, each extended term become effective. The results of the t-test show that each extended term has a significant difference in at least one evaluation criterion. This indicates that location and category information are independently effective.

The main point of our paper is to prove that location information and category information can improve the precision of Robertson’s probabilistic information retrieval method. This was confirmed by our experimental results.

Use of location information is apt to decrease the precision of B-Judgement. This is because B-Judgement judges that “a document whose topic is partly relevant to a query” is a relevant document. Location information weights a term which is in the title or at the beginning of the body of a document, i.e., a term which indicates the topic of a document. Therefore, for a document where the content of a query is written someplace than the topic part is not likely to be retrieved. The T-test also showed that location information is not significantly different in B-Judgement.

4.3 Effectiveness of detail terms

This section examines the effectiveness of the terms of $K_{\text{location}}$, $K_{\text{category}}$, and $K_{\text{detail}}$. In our experiments, the shortest terms method is used for term extraction. The values of the constants of the detail terms are set as in System B of Section 3. A comparison of the experimental results is shown in Table 3. The four terms $K_{\text{nado}}$, $K_{\text{num}}$, $K_{\text{hira}}$, $K_{\text{matsuri}}$, and $K_{\text{toho}}$ were used.
and $K_{\text{stopword}}$ did not improve precision, while $K_{\text{decr}}$ and $K_{\text{neg}}$ improved precision greatly. This indicates that the following were confirmed by experiments:

- A term which is obtained from a title of a query (DESCRIPTION) is important.
- A term which is obtained from an expression tagged with "NEG" should be removed.

## 5 Conclusion

Our information retrieval method uses Robertson’s 2-poisson model $\mathcal{P}$, which is one kind of probabilistic approach. But, this method does not use location or category information, which should be used to facilitate information retrieval. Against this background, we constructed a framework by using location, category and detailed information in a 2-poisson model. For the 1999 IREX contest, we submitted our two systems where their precision in the A-judgement measure was 0.4926 and 0.4827, respectively. The highest values among the 15 teams and 22 systems in the IREX contest. These results indicate that our method is comparatively good.

We carried out comparison experiments in order to confirm the effectiveness of each method used in our systems. We found that location and category information are effective while even the shortest terms method can obtain high precision. Also, we found several detailed facts such as an expression tagged with "NEG", should be removed.

After this work, by using the technique of IR, we are conducting the research on question answering system $\mathcal{Q}$.

## Acknowledgments

We would like to thank Dr. Naoto Takahashi of ETL in Japan for his comments on use of category information. In this work, we use a lot of data of IREX. We would like to thank the staff and participants at the IREX contest $\mathcal{C}$.

## References

1. Sumio Fujita. Notes on phrasal indexing JSCB evaluation experiments at IREX-IR. *Proceedings of the IREX Workshop*, pages 45–51, 1999.
2. Sadao Kurohashi and Makoto Nagao. *Japanese Morphological Analysis System JUMAN version 3.5*. Department of Informatics, Kyoto University, 1998. (in Japanese).
3. Mainichi Publishing. *Mainichi newspaper 1994-1995*, 1994.
4. Masaki Murata, Qing Ma, Kiyotaka Uchimoto, Hiromi Ozaku, Hitoshi Isahara, and Masao Utiyama. Information retrieval using location and category information. *Journal of the Association for Natural Language Processing*, 7(2), 2000. (in Japanese).
5. Masaki Murata, Kiyotaka Uchimoto, Hiromi Ozaku, and Qing Ma. Information retrieval based on stochastic models in IREX. *Proceedings of the IREX Workshop*, 1999. (in Japanese).
6. Masaki Murata, Masao Utiyama, and Hitoshi Isahara. Question answering system using syntactic information. 1999.
7. Tomohiro Ozawa, Mikio Yamamoto, Hideko Yamamoto, and Kyoji Umemaru. Word detection using the similarity measurement in information retrieval. *Proc. of the 5th Conference on Applied Natural Language Processing*, pages 305–308, 1999. (in Japanese).
8. S. E. Robertson and S. Walker. Some simple effective approximations to the 2-poisson model for probabilistic weighted retrieval. In *Proceedings of the Seventeenth Annual International ACM SIGIR Conference on Research and Development in Information Retrieval*, 1994.
9. S. E. Robertson, S. Walker, S. Jones, M. M. Hancock-Beaulieu, and M. Gatford. Okapi at trec-3. In *TREC-3*, 1994.
10. Gerard Salton and Chris Buckley. Improving retrieval performance by relevance feedback. In Karen Sparck Jones and Peter Willett, editors, *Readings in Information Retrieval*. Morgan Kaufmann Publishers, 1997.
11. Satoshi Sekine and Hitoshi Isahara. IREX project overview. *Proceedings of the IREX Workshop*, pages 7–12, 1999.
12. trec_eval. ftp://ftp.cs.cornell.edu/pub/smart. 1992.
Japanese Probabilistic Information Retrieval Using Location and Category Information

Masaki Murata, Qing Ma, Kiyotaka Uchimoto, Hiromi Ozaku, Masao Utiyama and Hitoshi Ishihara

Intelligent Processing Section, Kansai Advanced Research Center, Communications Research Laboratory, Ministry of Posts and Telecommunication 588-2, Iwaoa, Nishi-k, Kobe, 651-2402, Japan Phone: +81-78-969-2181 Fax: +81-78-969-2189 E-mail: murata@crl.go.jp http://www-karc.crl.go.jp/ips/murata

Abstract

Robertson's 2-poisson information retrieve model does not use location and category information. We constructed a framework using location and category information in a 2-poisson model. We submitted two systems based on this framework to the IREX contest, Japanese language information retrieval contest held in Japan in 1996. For precision in the A-judgement measure they scored 0.4926 and 0.4827, the highest values among the 15 teams and 22 systems that participated in the IREX contest. We describe our systems and the comparative experiments done when various parameters were changed. These experiments confirmed the effectiveness of using location and category information.

Keyword: 2-poisson model, Location information, Category information

1 Introduction

Information retrieval (IR) has become an increasingly important area of research due to the rapid growth of the Internet. In 1999 the Information Retrieval and Extraction Exercise contest (IREX) was held in Japan. We submitted two systems to this contest. Their precision in the A-judgement measure\(^1\) was 0.4926 and 0.4827, the highest values among the 15 teams and 22 systems in the IREX contest. This paper describes our systems and the comparative experiments done when various parameters were changed.

Our information retrieval method uses Robertson's 2-poisson model [8], which is one kind of probabilistic approach. But, Robertson's method does not use location or category information, which should be used to facilitate information retrieval. Against this background, we constructed a framework by using location information, category information, and detailed information in a 2-poisson model\(^2\). We verified the effectiveness of using these three types of information by doing comparative experiments. When the 2-poisson model is used a term extraction method needs to be selected. In this paper, we describe four term extraction methods, and compared them in experiments.

2 Information retrieval

2.1 Task

The information retrieval tasks in this paper are identical to those for the IREX contest. The database used for information retrieval (the same used in IREX) is from two-years (1994-1995) of a Japanese newspaper. We retrieved from this database documents which satisfied the information condition for a Japanese language query. The following is an example of a query. (The data is from the IREX preliminary experiment.)

Example of a Japanese query

\(<\text{TOPIC}>\)
\(<\text{TOPIC-ID}>1001</\text{TOPIC-ID}>\)
\(<\text{DESCRIPTION}>企業合併</\text{DESCRIPTION}>\)
\(<\text{NARRATIVE}>記日に企業合併事実の発表が述べられており、その合併に参加する企業の名前が確認できる事。また、合併企業の業績、目的など具体的内容のいずれかが確認できる事。企業合併は企業合併、企業統合、企業買収を含む。</\text{NARRATIVE}>\)
\(<\text{TOPIC}>\)

English translation

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. To copy otherwise, to republish, to post on servers or to redistribute to lists, requires prior specific permission and/or fee.

Proceedings of the 5th International Workshop Information Retrieval with Asian Languages

Copyright ACM 1-58113-300-4/00/0009 ... $5.00
2.2 Outline of our method

Our information retrieval method uses Robertson's 2-poisson model [8] which is one kind of probabilistic approach. Robertson's method calculates each document's score using the following equation*1, then outputs the documents with high scores as retrieval results. (The following $Score(d, q)$ is the score of a document $d$ against a query $q$.)

$$
Score(d, q) = \sum_{t \in q} \frac{tf(d, t) \times \log \frac{N}{df(t)}}{tf(d, t) + k_d \times \frac{\text{length}(d)}{\Delta}} \times \frac{tf(q, t)}{tf(q, t) + k_q}
$$

(1)

where terms occur in a query. $tf(d, t)$ is the frequency of a term $t$ in a document $d$, $tf(q, t)$ is the frequency of $t$ in a query $q$, $df(t)$ is the number of documents in which $t$ occurs, $N$ is the total number of documents, $\text{length}(d)$ is the length of a document $d$, and $\Delta$ is the average length of the documents. $k_d$ and $k_q$ are constants which are set by experiments.

In this equation, we call $\frac{tf(d, t)}{tf(d, t) + k_d}$ the TF term, (abbr. $TF(d, t)$), $\frac{\text{length}(d)}{\Delta}$ the IDF term, (abbr. $IDF(t)$), and $\frac{tf(q, t)}{tf(q, t) + k_q}$ the TFq term, (abbr. $TFq(q, t)$).

Our method adds several extended terms to this equation, and is expressed by the following equation.

$$
Score(d, q) = K_{category}(d) \left\{ \sum_{t \in q} (TF(d, t) \times IDF(t)) \times TFq(q, t) \times K_{detail}(d, t) \times K_{location}(d, t) \right\} + \frac{\text{length}(d)}{\Delta}
$$

(2)

The TF, IDF and TFq terms in this equation are identical to those in Eq. (1). The term $\frac{\text{length}(d)}{\Delta}$ has a higher value when a document is longer. This term is made because if the other information is exactly equal, the longer document is more likely to include the content requested by the query. $K_{category}$, $K_{detail}$ and $K_{location}$ are extended numerical terms made to improve precision. $K_{category}$ uses the category information of the document found in newspapers, such as the economic and political pages. $K_{location}$ uses the location of the term in the document. If a term is in the title or at the beginning of the body of the document, it is given a higher weighting. $K_{detail}$ uses the information such as whether the term is a proper noun and or a stop word such as に the “document” and もの “thing”. In the next section, we explain these extended numerical terms in detail.

2.3 Extended numerical terms

We use the three extended numerical terms of $K_{location}$, $K_{category}$ and $K_{detail}$ as in Eq. (2). This section explains them in detail.

---

*1This equation is BM11, which corresponds to BM25 in the case of $b = 1.2$. Although we made experiments testing some cases of $b$ in BM25, the case of $b = 1$ was roughly better than any other cases in this work. So we used BM11.
1. **Location information (K\textsubscript{location})**

In general, the title or the first sentence of the body of a document in a newspaper very often indicates its subject. Therefore, the precision of information retrieval can be improved by weighting the terms in these two locations. The term \( K_{\text{location}} \) performs this task, and changes the weight of a term based its location at the beginning of the document. If a term is in the title or at the beginning of the body, it is given a high weighting. Otherwise, it is given low weighting. This term is expressed as follows:

\[
K_{\text{location}}(d, t) = \begin{cases} 
  k_{\text{location},1} & \text{(when a term } t \text{ occurs in the title of a document } d), \\
  1 + k_{\text{location},2} & \text{(length}(d) - 2 \times P(d, t))^{3} \text{ length}(d) \end{cases} 
\]

\( P(d, t) \) is the location where a term \( t \) occurs in the document \( d \). When a term occurs more than once in a document, its first occurrence is used. \( k_{\text{location},1} \) and \( k_{\text{location},2} \) are constants which are set by experiments.

2. **Category information (K\textsubscript{category})**

\( K_{\text{category}} \) uses category information such as the economic and political pages. This functions as a technique called relevance feedback [10]. First, we specify the categories which occur in the top 100 documents of the first retrieval when \( K_{\text{category}} = 1 \). Then, we increase the scores of documents having the same categories. For example, if economic pages often occur in the top 100 documents of the first retrieval, we increase the score of a document whose page is an economic page and decrease the score of the document whose page is different. \( K_{\text{category}} \) is expressed as follows:

\[
K_{\text{category}}(d) = 1 + k_{\text{category}} \frac{(\text{RatioA}(d) - \text{RatioB}(d))}{(\text{RatioA}(d) + \text{RatioB}(d))} 
\]

where \( \text{RatioA} \) is the ratio of a category in the top 100 documents of the first retrieval, \( \text{RatioB} \) is the ratio of a category in all the documents. The value of \( K_{\text{category}}(d) \) is large when \( \text{RatioA} \) is large (page of a document \( d \) occurs frequently in the top 100 documents of the first retrieval) and \( \text{RatioB} \) is small (page of a document \( d \) does not occur often in all the documents). \( K_{\text{category}} \) is a constant which is set by experiments.

3. **Other information (K\textsubscript{detail})**

\( K_{\text{detail}} \) is a more detailed numerical term that uses different information, such as whether the term is a proper noun and whether the term is a stop word such as 文書 “document” and メン の “thing”. If a term is a proper noun, it is weighted high. If a term is a stop word, such as 文書 “document” and メン の “thing”, it is weighted low. \( K_{\text{detail}} \) is expressed as follows for simplicity; the variables for a document and a term, \( d \) and \( t \), are omitted:

\[
K_{\text{detail}} = K_{\text{decr}} \times K_{\text{proper}} \times K_{\text{nado}} \times K_{\text{num}} \times K_{\text{hiragana}} \times K_{\text{neg}} \times K_{\text{stopword}}
\]

Each term in this equation is explained below.

- \( K_{\text{decr}} \)
  When a term is obtained from the title of a query, i.e. DESCRIPTION, \( K_{\text{decr}} = K_{\text{decr}}(<1) \). Otherwise, \( K_{\text{decr}} = 1 \). This is because a term obtained from the title of a query is important.

- \( K_{\text{proper}} \)
  When a term is a proper noun, \( K_{\text{proper}} = K_{\text{proper}}(<1) \). Otherwise, \( K_{\text{proper}} = 1 \). This is because a term that is a proper noun is important.

- \( K_{\text{nado}} \)
  When a term is followed by the Japanese word nado (such as) in a query sentence, \( K_{\text{nado}} = K_{\text{nado}}(<1) \). Otherwise, \( K_{\text{nado}} = 1 \). A term which is followed by the Japanese word nado is specific in meaning and is just as important as a proper noun.

- \( K_{\text{num}} \)
  When a term is numeric, \( K_{\text{num}} = K_{\text{num}}(<1) \). Otherwise, \( K_{\text{num}} = 1 \). A term which consists of only numerals does not contain much relevant information making it unimportant to a query.

- \( K_{\text{hiragana}} \)
  When a term consists of hiragana characters only, \( K_{\text{hiragana}} = K_{\text{hiragana}}(<1) \). Otherwise, \( K_{\text{hiragana}} = 1 \). A term which consists of only hiragana characters does not contain much relevant information making it unimportant to a query.

- \( K_{\text{neg}} \)
  When a term is obtained from a region tagged with a NEG tag in a query, \( K_{\text{neg}} = K_{\text{neg}}(<1) \). Otherwise, \( K_{\text{neg}} = 1 \). In a query of the IREX contest, an expression, “... wa nozoki” (... is excepted), as in the following query, was tagged with a NEG tag.

Example Japanese query

\(<\text{TOPIC}>\)
\(<\text{TOPIC>-ID}>1003</\text{TOPIC>-ID}>\)
\(<\text{DESCRIPTION}>\)国連軍の派遣</DESCRIPTION>\)
\(<\text{NARRATIVE}>平和維持活動など国連の活動における国連軍の派遣について述べられている記事。派遣の目的または対象地域が記事から明示的に分かる。</\text{NARRATIVE}>\)

English translation

\(<\text{TOPIC}>\)
\(<\text{TOPIC>-ID}>1003</\text{TOPIC>-ID}>\)
\(<\text{DESCRIPTION}>\)Dispatch of the United Nations forces</DESCRIPTION>\)
\(<\text{NARRATIVE}>The condition for a relevant document is that in the document a dispatch of the United Nations forces in the activity of UN such as peace maintenance activity is described. The purpose of the dispatch or the target region should be described. A document describing the discussion of whether the Self-Defense Forces of Japan is dispatched to UN or not is eliminated.</\text{NARRATIVE}>\)
If a term from a region tagged with a NEG tag is used, non-relevant documents are often retrieved and therefore such a term is weighted low. In this paper, \( k_{\text{neg}} \) is set to 0. This indicates that a term from a region tagged with a NEG tag is not used in retrieval.

- \( K_{\text{stopword}} \)
  When a term is a stopword such as *jouken* (condition), *kaji* (document), and *boai* (case), \( K_{\text{stopword}} = K_{\text{stopword}}(< 1) \). Otherwise \( K_{\text{stopword}} = 1 \). A term that is a stopword is unimportant.

Each constant, such as \( k_{\text{descr}} \), is set experimentally.

### 2.4 How to extract terms

Before being able to use Eq. (2) in information retrieval, we must extract the terms from a query. This section describes how to do this. With regard to term extraction, we considered the several methods listed below.

1. Method using only the shortest terms
   This is the simplest method. The method divides the query sentence into short terms by using the morphological analyzer “jumao” [2] and eliminates non-nominal words and stop words.
   The remaining words are used in the retrieval process.

2. Method using all term patterns
   In the first method the terms are too short. For example, “enterprise” and “amalgamation” are used instead of “enterprise amalgamation.”
   We thought that we should use “enterprise amalgamation” in addition to the two short terms. Therefore, we decided to use both short and long terms. We call this “all-term patterns method.”
   For example, when “enterprise amalgamation materialization” was inputted, we use “enterprise”, “amalgamation”, “materialization”, “enterprise amalgamation”, “amalgamation materialization”, and “enterprise amalgamation materialization” as terms for information retrieval. We thought that this method would be effective because it uses all term patterns.

3. Method using a lattice
   Although the method using all-term patterns is effective for use with all patterns of terms, it needs to be normalized by using the adhoc equation \( \sqrt{\frac{n(n+1)}{2}} \).
   Thus, we considered the method where all the term patterns are stored into a lattice structure. We use the patterns in the path where the score in Eq. (2) is the highest. (This method is almost same as Ozawa’s [7]. The differences are the fundamental equation for information retrieval, and whether to use or not use a morphological analyzer.)

   For example, in the case of “enterprise amalgamation materialization” a lattice, as shown in Fig. 1, is obtained. As in this figure, four paths exist where each of their scores are calculated by Eq. (2) and the terms in the highest path are used. This method does not require the adhoc normalization as in the method using all the term patterns.

4. Method using down-weighting [1]
   This is the method that Fujita proposed at the IREX contest, and we examined after the contest.
   It is similar to the all-term patterns method. It uses all the term patterns but the normalization is different from the all-term patterns method. It does not change the weight of the shortest terms, and decreases weight of the longer terms. We decided to multiply the weight \( k_{\text{down}} \) to a term, when it consisted of \( x \) shortest terms, where \( k_{\text{down}} \) was set by experiments. This method basically uses the shortest terms while also using the longer terms by down-weighting them.

### 3 IREX contest results

For our two submissions to the IREX contest, we selected the “all-term patterns” and “lattice structure” methods to extract terms, and set the constants of the extended terms in order to maximize the precision in the preliminary-run data as follows.

1. **System A**
   It used the lattice method for the term extraction. The parameters were set as follows: \( k_{\text{location},1} = 1.35 \), \( k_{\text{location},2} = 0.125 \), \( k_{\text{category}} = 0 \), \( k_{\text{descr}} = 1.5 \), \( k_{\text{proper}} = 2 \), \( k_{\text{nao}} = 1 \), \( k_{\text{num}} = 0.5 \), \( k_{\text{area}} = 0.5 \), \( k_{\text{neg}} = 0 \), \( k_{\text{stopword},1} = 0 \), \( k_{\text{stopword},2} = 0.5 \), \( k_{\text{t}} = 1 \).

---

4Sino, Japanese is an agglutinative language like Chinese, there are no spaces between words and a morphological analyzer is necessary to divide a sentence into words.

5Although this paper deals only with Japanese, not English, for this explanation we use English examples for the English moders. This method handles compound nouns and can be used not only for Japanese but also for English.

6IREX allowed two systems to be submitted.

7The reason we did not use “the shortest terms method” is because it is too simple and did not seem effective. The “down-weighting method” is a method proposed at IREX. So we could not use it in IREX.
| System ID | A-Judgment | B-Judgment |
|-----------|------------|------------|
| 1108a     | 0.4505     | 0.4588     |
| 1108b     | 0.4657     | 0.5201     |
| 1106      | 0.2960     | 0.2120     |
| 1110      | 0.3228     | 0.4276     |
| 1112      | 0.2790     | 0.3343     |
| 1120      | 0.2713     | 0.3399     |
| 1122a     | 0.3808     | 0.4689     |
| 1122b     | 0.4034     | 0.4747     |
| 1126      | 0.0066     | 0.0891     |
| 1128a     | 0.3384     | 0.3897     |
| 1128b     | 0.3924     | 0.4175     |
| 1132      | 0.0602     | 0.0791     |
| 1133a     | 0.2933     | 0.2277     |
| 1133b     | 0.2457     | 0.2248     |
| 1135a     | 0.4926     | 0.5119     |
| 1135b     | 0.4871     | 0.4878     |
| 1142      | 0.4455     | 0.4929     |
| 1144a     | 0.4638     | 0.5510     |
| 1144b     | 0.4592     | 0.5442     |
| 1145a     | 0.3352     | 0.3424     |
| 1145b     | 0.2553     | 0.2935     |
| 1146      | 0.2220     | 0.2742     |

and \( K_p = 0.1 \). Terms obtained from DESCRIPTION are handled as terms different from terms obtained from NARRATIVE.

2. System B

It used all-term patterns method for term extraction. The parameters were set as follows: \( k_{\text{location}} = 1.3, k_{\text{category}} = 0.1, k_{\text{descr}} = 1.75, k_{\text{proper}} = 2, k_{\text{rado}} = 1.7, k_{\text{num}} = 0.5, k_{\text{hiru}} = 0.5, k_{\text{neg}} = 0, k_{\text{proper}2} = 0, k_{\text{tagnum}2} = 0.5, k_0 = 1, \) and \( k_b = 0 \). Terms obtained from DESCRIPTION were handled as the terms different from those obtained from NARRATIVE.

In the contest, the results for the 22 systems were submitted by the 15 teams. Their R-Precisions are shown in Table 1. The first column of the table indicates the names of the systems. Our two systems, System A and System B correspond to 1135a and 1135b. A-Judgment and B-Judgement are the evaluation criteria determined by the IREX committee. A-Judgment means that a document whose topic is relevant to a query is judged as a relevant document. B-Judgment means that a document whose topic is partly relevant to a query is also judged as a relevant document. Although our systems were not the highest in B-Judgment, they were the highest among all the systems in A-Judgment. This result indicates that our method is relatively superior.

4. Experiments

In this section we describe several experiments done to test the effectiveness of the several methods used in our system. In the experimental results of this section, we also show Average Precision (the average of the precision when each relevant document is retrieved) in addition to R-Precision. For the comparison experiments, \( t \)-test is used. A method tagged with "#" in Tables 2 to 4 is the base for comparison. A method tagged with "\#" is superior to the base method at the significance level of 5%, and a method tagged with "*=" is superior at the significance level of 1%. T-test is used only in formal-run experiments. (The preliminary-run data contained six queries, and the formal-run data contained thirteen queries.)

4.1 Comparison of term extraction methods

We showed the following four term extraction methods in Section 2.4.

1. Method using the shortest terms
2. Method using all the term patterns
3. Method using a lattice
4. Method using down-weighting

All the comparison results are shown in Table 2. In Table 2(a) all extended terms were used. In Table 2(b) no extended terms were used. In the down-weighting method we tested the two cases of \( k_{\text{down}} = 0.1 \) and \( k_{\text{down}} = 0.01 \).

The precision of the all-term patterns method was lowest in the formal run. It needed to be normalized using the ad hoc equation. Since it had the lowest precision, it was thought to be inferior to the other methods. Also, it was shown by \( t \)-test to be significantly inferior to the shortest terms method.

Although the down-weighting method obtained the highest precision when no extended terms were used, it was not as effective when all the extended terms were used. Since it was significantly different from any of the other methods, cannot say that it is very reliable. But, in the case where a small amount of retrieval information was used (i.e. no extended terms) it was very effective. Since only the shortest term method is significantly different from the all-term patterns method, we think that they must have some problems. One problem that occurred when using the lattice method was that the terms used in retrieval had been mostly very heavy, depending on the context, while the down-weighting method's problem was that it used the extra terms even if it down-weights them. However, it is thought by us that using longer terms in addition, is better than using only the shortest terms. We have to continue the investigation of term extractions.

4.2 Effectiveness of extended terms

Extended terms used in this paper are classified into the following three categories:

1. \( k_{\text{location}} \) (location information)
2. \( k_{\text{category}} \) (category information)
3. \( k_{\text{detail}} \) (detail information)

(Here, \( k_{\text{detail}} \) contains \( k_{\text{length}} = \frac{\text{length}}{\text{length} + 3} \), which is the numerical term for a document length in Eq. (2).)

In order to verify the effectiveness of the above three extended terms, we carried out eight experiments in which these three terms were alternately used or not.
Table 2: Comparison of methods to extract keywords
(a) When all extended terms are used

| Method to extract terms | Formal run | Preliminary run |
|-------------------------|------------|-----------------|
|                         | R-Precision | Average precision | R-Precision | Average precision |
|                         | A-Judge | B-Judge | A-Judge | B-Judge | A-Judge | B-Judge | A-Judge | B-Judge |
| Using the shortest terms | 0.5012 | 0.5205** | 0.4885** | 0.4764** | 0.4112 | 0.4542 | 0.4516 | 0.5151 |
| Using all term patterns | 0.4377 | 0.4678 | 0.4553 | 0.443 | 0.4373 | 0.5573 | 0.4576 | 0.5127 |
| Using the lattice structure | 0.4296 | 0.5119 | 0.498 | 0.4698 | 0.4299 | 0.5699 | 0.4638 | 0.5170 |
| Using down-weight (kedown = 0.01) | 0.5006 | 0.5217 | 0.4935 | 0.4778 | 0.4112 | 0.5445 | 0.4546 | 0.5157 |
| Using down-weight (kedown = 0.1) | 0.4997 | 0.5223 | 0.4899 | 0.4809 | 0.4748 | 0.5504 | 0.4563 | 0.5185 |

(b) When no extended terms are used

| Method to extract terms | Formal run | Preliminary run |
|-------------------------|------------|-----------------|
|                         | R-Precision | Average precision | R-Precision | Average precision |
|                         | A-Judge | B-Judge | A-Judge | B-Judge | A-Judge | B-Judge | A-Judge | B-Judge |
| Using the shortest terms | 0.4741 | 0.4899 | 0.4488 | 0.4487 | 0.5000 | 0.5082 | 0.5000 | 0.4468 |
| Using all term patterns | 0.4445 | 0.4660 | 0.4172 | 0.4380 | 0.2905 | 0.4981 | 0.3900 | 0.4444 |
| Using the lattice structure | 0.4711 | 0.4884 | 0.4436 | 0.4448 | 0.4099 | 0.5069 | 0.3884 | 0.4469 |
| Using down-weight (kedown = 0.01) | 0.4706 | 0.4896 | 0.4492 | 0.4494 | 0.2940 | 0.5082 | 0.3850 | 0.4470 |
| Using down-weight (kedown = 0.1) | 0.4816 | 0.4986 | 0.4515 | 0.4518 | 0.4003 | 0.2076 | 0.3380 | 0.4488 |

The method tagged with "#" is a base method for comparison. A result tagged with "*" is superior to the base method at the significance level of 5%, and a result tagged with "**" is superior at the significance level of 1%.

Table 3: Comparison of extended numerical terms
(a) Comparison when using the lattice method

| Numerical terms | Formal run | Preliminary run |
|-----------------|------------|-----------------|
|                 | R-Precision | Average precision | R-Precision | Average precision |
|                 | A-Judge | B-Judge | A-Judge | B-Judge | A-Judge | B-Judge | A-Judge | B-Judge |
| yes yes yes | 0.5031 | 0.5181 | 0.4888** | 0.4785 | 0.4265 | 0.5417 | 0.4282 | 0.4572 |
| yes yes no | 0.4764 | 0.4935 | 0.4619 | 0.4375 | 0.4092 | 0.5086 | 0.4207 | 0.4624 |
| yes no yes | 0.4926 | 0.5119 | 0.4898** | 0.4698 | 0.4399 | 0.5499 | 0.4638 | 0.5170 |
| no yes yes | 0.4989** | 0.5031** | 0.4731** | 0.4566** | 0.4421 | 0.5618 | 0.4833 | 0.5171 |
| yes no no | 0.4932 | 0.4984 | 0.4789** | 0.4519 | 0.4308 | 0.5083 | 0.4285 | 0.4638 |
| no yes no | 0.4931 | 0.5084** | 0.4651** | 0.4654** | 0.4085 | 0.5134 | 0.3945 | 0.4554 |
| no no no | 0.4979** | 0.5277** | 0.4637 | 0.4829** | 0.4407 | 0.5603 | 0.4391 | 0.5127 |

(b) Comparison when using the shortest terms method

| Numerical terms | Formal run | Preliminary run |
|-----------------|------------|-----------------|
|                 | R-Precision | Average precision | R-Precision | Average precision |
|                 | A-Judge | B-Judge | A-Judge | B-Judge | A-Judge | B-Judge | A-Judge | B-Judge |
| yes yes yes | 0.5012 | 0.5205** | 0.4935** | 0.4764 | 0.4412 | 0.5442 | 0.4516 | 0.5151 |
| yes yes no | 0.4967 | 0.4976 | 0.4704 | 0.4464 | 0.4126 | 0.5136 | 0.4220 | 0.4619 |
| yes no yes | 0.5017 | 0.5094 | 0.4850 | 0.4740 | 0.4410 | 0.5517 | 0.4556 | 0.5084 |
| no yes yes | 0.4991 | 0.5325** | 0.4799 | 0.4841** | 0.4213 | 0.5616 | 0.4340 | 0.5096 |
| yes no no | 0.4983 | 0.4952 | 0.4647 | 0.4444 | 0.4247 | 0.5076 | 0.4200 | 0.4614 |
| no yes no | 0.4924* | 0.4900* | 0.4537 | 0.4500 | 0.3927 | 0.5119 | 0.3901 | 0.4517 |
| no no yes | 0.4970 | 0.5242** | 0.4693* | 0.4904* | 0.4198 | 0.5596 | 0.4332 | 0.5070 |
| no no no | 0.4744 | 0.4897 | 0.4488 | 0.4487 | 0.3900 | 0.5082 | 0.3850 | 0.4468 |

used. These experiments were performed using "the lattice method" and "the shortest terms method". The results are shown in Table 3.

The last line of the table is the case where no extended terms were used and the first line of the table is the case where they were all used. When we compared the two lines, we found there was an improvement of 0.077 to 0.045 when our extended terms were used. (For example, the average precision of A-Judgement of the shortest terms method improved from 0.4488 to 0.4935, i.e., 0.0447.) This indicates that the extended terms used in our experiment were totally effective. Retrieval precision can be improved by using location and category information in addition to Robertson's probabilistic retrieval method.

A method that uses one of the extended terms is more precise than one using no extended terms. Thus, each extended term become effective. The results of the t-test show that each extended term has a significant difference in at least one evaluation criterion. This indicates that location and category information are independently effective.

The main point of our paper is to prove that location information and category information can improve the precision of Robertson's probabilistic information retrieval method. This was confirmed by our experimental results.

Use of location information is apt to decrease the precision of B-Judgement. This is because B-Judgement judges that "a document whose topic is partly relevant to a query" is a relevant document. Location information weighs a term which is in the title or at the beginning of the body of a document, i.e., a term which indicates the topic of a document. Therefore, for a document where the content of a query is written somewhere else than the topic part is not likely to be retrieved. The T-test also showed that location information is not significantly different in B-Judgement.
| Detail terms | R-Precision | Average precision | Preliminary run |
|-------------|-------------|------------------|-----------------|
|             | A-Judge | B-Judge | A-Judge | B-Judge | A-Judge | B-Judge | A-Judge | B-Judge | A-Judge | B-Judge |
| Neither*   | 0.4744  | 0.4879  | 0.4488  | 0.4487  | 0.3900  | 0.3605  | 0.3880  | 0.4488  |
| Kdco only  | 0.4878  | 0.5125** | 0.4614* | 0.4674** | 0.4136  | 0.3336  | 0.3930  | 0.4635  |
| Kpro only  | 0.4746  | 0.4940  | 0.4481  | 0.4523  | 0.4001  | 0.3533  | 0.4172  | 0.4765  |
| Knao only  | 0.4630  | 0.4765  | 0.4834  | 0.4303  | 0.3973  | 0.5007  | 0.3859  | 0.4487  |
| Khiro only | 0.4744  | 0.4897  | 0.4488  | 0.4487  | 0.4019  | 0.5134  | 0.4067  | 0.4554  |
| Kneg only  | 0.4878  | 0.5037** | 0.4603  | 0.4628* | 0.3968  | 0.5295  | 0.3985  | 0.4629  |
| Kstepward only | 0.4713  | 0.4941  | 0.4507  | 0.4548** | 0.3945  | 0.5088  | 0.3809  | 0.4488  |
| Klenth only | 0.4775  | 0.4880  | 0.4472  | 0.4492  | 0.3900  | 0.3605  | 0.3880  | 0.4488  |

### 4.3 Effectiveness of detail terms

This section examines the effectiveness of the terms of\(K_{\text{detail}}\) and\(K_{\text{length}}\). In our experiments, the shortest terms method is used for term extraction. The values of the constants of the detail terms are set as in System B of Section 3. A comparison of the experimental results is shown in Table 4. The four terms \(K_{\text{nao}}, K_{\text{nao-f}}, K_{\text{hiro}},\) and \(K_{\text{stepward}}\) did not improve precision, while \(K_{\text{dco}}\) and \(K_{\text{neg}}\) improved precision greatly. This indicates that the following were confirmed by experiments:

- A term which is obtained from a title of a query (DESCRIPTION) is important.
- A term which is obtained from a expression tagged with "NEG" should be removed.

### 5 Conclusion

Our information retrieval method uses Robertson's 2-poisson model [8], which is one kind of probabilistic approach. But, this method does not use location or category information, which should be used to facilitate information retrieval. Against this background, we constructed a framework by using location, category and detailed information in a 2-poisson model. For the 1999 IREX contest, we submitted our two systems where their precision in the A-judgement measure was 0.4926 and 0.4877, the highest values among the 15 teams and 22 systems in the IREX contest. These results indicate that our method is comparatively good.

We carried out comparison experiments in order to confirm the effectiveness of each method used in our systems. We found that location and category information are effective while even the shortest terms method can obtain high precision. Also, we found several detailed facts such as an expression tagged with "NEG", should be removed.

After this work, by using the technique of IR, we are conducting the research on question answering system [6].

### Acknowledgments

We would like to thank Dr. Naoto Takehashi of ETL in Japan for his comment on use of category information. In this work, we use a lot of data of IREX. We would like to thank the staff and participants at the IREX contest [11, 5, 4].

### References

[1] Sumio Fujita. Notes on phrasal indexing. JSCB evaluation experiments at IREX-IR. Proceedings of the IREX Workshop, pages 46–51, 1999.

[2] Sadao Kurohashi and Makoto Nagao. Japanese Morphological Analysis System JUMAN version 3.5. Department of Informatics, Kyoto University, 1998. (in Japanese).

[3] Mainichi Publishing. Mainichi newspaper 1994-1994, 1994.

[4] Masaki Murata, Qing Ma, Kiyotaka Uchimoto, Hiromi Ozaku, Hitoshi Iwashara, and Masao Utiyama. Information retrieval using location and category information. Journal of the Association for Natural Language Processing, 7(2), 2000. (in Japanese).

[5] Masaki Murata, Kiyotaka Uchimoto, Hiromi Ozaku, and Qing Ma. Information retrieval based on stochastic models in IREX. Proceedings of the IREX Workshop, 1999. (in Japanese).

[6] Masaki Murata, Masao Utiyama, and Hitoshi Iwashara. Question answering system using syntactic information, 1999. http://xxx.lanl.gov/abs/cs.CL/9911006.

[7] Tomohiro Ozawa, Mikio Yamamoto, Hideko Yamamoto, and Kyoji Umemuro. Word detection using the similarity measurement in information retrieval, Proc. of the 5th Conference on Applied Natural Language Processing, pages 305–308, 1999. (in Japanese).

[8] S. E. Robertson and S. Walker. Some simple effective approximations to the 2-poisson model for probabilistic weighted retrieval. In Proceedings of the Seventeenth Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, 1994.

[9] S. E. Robertson, S. Walker, S. Jones, M. M. Hancock-Beaulieu, and M. Cutt. Okapi at trec-3. In TREC-3, 1994.

[10] Gerard Salton and Chris Buckley. Improving retrieval performance by relevance feedback. In Karen Spark Jones and Peter Willett, editors, Readings in Information Retrieval, Morgan Kaufmann Publishers, 1997.
[11] Satoshi Sekine and Hitoshi Isahara. IREX project overview. Proceedings of the IREX Workshop, pages 7-12, 1999.

[12] tree.eval ftp://ftp.cs.cornell.edu/pub/smart. 1992.