Japanese Probabilistic Information Retrieval Using Location and Category Information

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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

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 2poisson 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 2poisson model². We verified the effectiveness of using

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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.

these three types of information by doing comparative

Information retrieval

2.1Task

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 [3]. 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></DESCRIPTION> <NARRATIVE></NARRATIVE> </TOPIC>

English translation

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

tion in addition to Robertson's probabilistic information retrieval

A-judgment means that a document whose topic is relevant

to a query is judged a relevant document. 2 The reason that this paper is entitled "Probabilistic Information Retrieval Using Location Information and Category Information" is that our methods use location and category informa-

<NARRATIVE>

The condition for a relevent 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. </NARRATIVE> </TOPIC>

The number indicated by <TOPIC-ID> means the ID number of the query. <DESCRIPTION> contains a phrase that indicates the information needed. contains the sentences that restrict the information requested. During the task, the system receives a query such as the above one and outputs 300 documents in order of confidence.

Example of a Japanese document

<DOCNO>950217091</DOCNO> <SECTION></SECTION> <HEADLINE></HEADLINE> <TEXT>

</TEXT> </DOC>

</DOC>

English translation

<DOCNO>950217091</DOCNO>

<SECTION>Economic page</SECTION>

<HEADLINE>Tounen company completely makes Kigunasu company a subsidiary company </HEADLINE> <TEXT> Tounen company anounced that it makes Kigunasu comapry, one of its group companies, (The capital is one billion yen. The head office is in Kawasaki city. The president is Mr. Toshihide Mori.) a completely subsidiary company. Kigunasu company is invested 70% by Tounen company and 30% by Nichimou company, and Tounen company purchases 600,000 stocks which Nichimou company possesses at 12,500,000,000 yens. </TEXT>

In this document, the newspaper information category (the economic or political pages) is indicated by <SECTION>, the title of the document is indicated by <HEADLINE>, and the body of the document is indicated by <TEXT>. The tool "trec_eval" of TREC is used to evaluate the retrieval results [12]. In the contest, "R-Precision" were used. It indicates the precision when retrieving R documents, where R is the number of relevant documents.

2.2Outline of our method

Our information retrieval method uses Robertson's 2poisson model [8] which is one kind of probabilistic approach. Robertson's method calculates each document's score using the following equation³, then outputs the documents with high scores as retrieval results. (The following Score(d, q) is the score of a document d against a

$$Score(d,q) = \sum_{\substack{\text{term } t \\ \text{in } q}} \left(\frac{tf(d,t)}{tf(d,t) + k_t \frac{length(d)}{\Delta}} \log \frac{N}{df(t)} \right)$$

$$\frac{tf_q(q,t)}{tf_q(q,t) + kq}$$

$$(1)$$

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

In this equation, we call $\frac{tf(d,t)}{tf(d,t)+k_t}$ the TF term, (abbr. TF(d,t)), $\log \frac{N}{df(t)}$ the IDF term, (abbr. IDF(t)), and $\frac{tf_q(q,t)}{tf_q(q,t)+k_q}$ the TF $_q$ term, (abbr. $TF_q(q,t)$).

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

$$Score(d.q) = K_{category}(d) \begin{cases} \sum_{\text{term } t} (TF(d,t) \ IDF(t) \end{cases}$$
$$TF_{q}(q,t) \ K_{detail}(d,t) \ K_{location}(d,t))$$
$$+ \frac{length(d)}{length(d) + \Delta} \end{cases}$$
(2)

The TF, IDF and TF_q terms in this equation are identical to those in Eq. (1). The term $\frac{length}{length+\Delta}$ 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 "document" and "thing". In the next section, we explain these extended numerical terms in detail.

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

 $^{^3}$ This equation is BM11, which corresponds to BM25 in the case of b = 1[9]. 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.

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:

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

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 a economic page and decrease the score of the document whose page is different. $K_{category}$ is expressed as follows;

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

where RatioA is the ratio of a category in the top 100 documents of the first retrieval. RatioB is the ratio of a category in all the documents. The value of $K_{category}(d)$ is large, when RatioA is large (page of a document d occurs frequently in the top 100 documents of the first retrieval.) and 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:

$$K_{detail} = K_{descr}K_{proper}K_{nado}K_{num}$$

$$K_{hira}K_{neg}K_{stopword}$$
 (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_{nun}

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></DESCRIPTION>
<NARRATIVE><NEG></NEG></NARRATIVE>
</TOPIC>

English translation

<TOPIC>

<TOPIC-ID>1003</TOPIC-ID> <DESCRIPTION>Dispatch of the United Nations forces</DESCRIPTION> <NARRATIVE>The condition for a relevent document is that in the document a dispatch of the United Nations forces in the activity of UN such as peace maintainence 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 elimated. </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 baai (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" [2] and eliminates non-nominal words and stop words⁴. 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 $\sqrt{\frac{n(n+1)}{2}}$, 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 $\sqrt{\frac{n(n+1)}{2}}$. 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.

Figure 1: An example of a lattice structure

(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 the weight of the longer terms. We decided to multiply the weight $k_{down}^{\ x-1}$ to a term, when it consisted of x shortest 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 contest⁶, we selected the "all-term patterns" and "lattice structure" methods to extract terms⁷, 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; $k_{location,1} = 1.35, k_{location,2} = 0.125, k_{category} = 0, k_{descr} = 1.5, k_{proper} = 2, k_{nado} = 1, k_{num} = 0.5, k_{hira} = 0.5, k_{neg} = 0, k_{stopword,1} = 0, k_{stopword,2} = 0.5, k_t = 1, and k_q = 0.1$. Terms obtained from DESCRIPTION are handled as terms different from terms obtained from NARRATIVE.

2. System B

⁴Since, 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.

⁵Although 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.

⁶ IREX allowed two systems to be submitted.

⁷ The reason we did not use "the shortest terms method" is because it is too simple and did not seem effective. The "downweighting method" is a method proposed at IREX. So we could not use it in IREX.

Table 1: R-Precision of all the systems

System ID	A-Judgment	B-Judgment
1103a	0.4505	0.4888
1103b	0.4657	0.5201
1106	0.2360	0.2120
1110	0.3329	0.4276
1112	0.2790	0.3343
1120	0.2713	0.3339
1122a	0.3808	0.4689
1122b	0.4034	0.4747
1126	0.0966	0.0891
1128a	0.3384	0.3897
1128b	0.3924	0.4175
1132	0.0602	0.0791
1133a	0.2383	0.2277
1133b	0.2457	0.2248
1135a	0.4926	0.5119
1135b	0.4827	0.4878
1142	0.4455	0.4929
1144a	0.4658	0.5510
1144b	0.4592	0.5442
1145a	0.3352	0.3424
1145b	0.2553	0.2935
1146	0.2220	0.2742

It used all-term patterns method for term extraction. The parameters were set as follows; $k_{location,1} = 1.3$, $k_{location,2} = 0.15$, $k_{category} = 0.1$, $k_{descr} = 1.75$, $k_{proper} = 2$, $k_{nado} = 1.7$, $k_{num} = 0.5$, $k_{hira} = 0.5$, $k_{neg} = 0$, $k_{stopword,1} = 0$, $k_{stopword,2} = 0.5$, $k_t = 1$, and $k_q = 0$. 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-Judgement 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 $k_{down}=0.1$ 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 $K_{length} = \frac{length}{length+\Delta}$ 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 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 0.027 to

Table 2: Comparison of methods to extract keywords

(a) When an extended terms are asea										
		Forma	al run			Prelimir	nary run			
Method to extract terms	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**	0.4935**	0.4764*	0.4412	0.5442	0.4546	0.5151		
Using all term patterns#	0.4827	0.4878	0.4553	0.4453	0.4373	0.5573	0.4576	0.5317		
Using the lattice structure	0.4926	0.5119	0.4808	0.4698	0.4599	0.5499	0.4638	0.5170		
Using down-weight $(k_{down} = 0.01)$ 0.500		0.5217	0.4935	0.4778	0.4412	0.5445	0.4546	0.5157		
Using down-weight $(k_{down} = 0.1)$	0.4997	0.5233	0.4939	0.4809	0.4478	0.5504	0.4563	0.5185		

(b) When no extended terms are used

		Form	al run		Preliminary run				
Method to extract terms	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	0.4744	0.4897	0.4488^*	0.4487^*	0.3900	0.5082	0.3850	0.4468	
Using all term patterns [#]	0.4445	0.4665	0.4172	0.4180	0.3965	0.4981	0.3960	0.4444	
Using the lattice structure	0.4711	0.4884	0.4436	0.4448	0.4009	0.5069	0.3884	0.4469	
Using down-weight $(k_{down} = 0.01)$	0.4760	0.4896	0.4492	0.4494	0.3940	0.5082	0.3850	0.4470	
Using down-weight $(k_{down} = 0.1)$	0.4816	0.4986	0.4545	0.4568	0.4003	0.5076	0.3860	0.4498	

The method tagged with "#" is a base method for comparison. A result tagged with "*" is superior to the base method's 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

				Form	al run			Prelimir	nary run	
Nur	nerical ter	ms	R-Precision		Average precision		R-Pre	cision	Average precision	
$K_{location}$	$K_{category}$	K_{detail}	A-Judge	B-Judge	A-Judge	B-Judge	A-Judge	B-Judge	A-Judge	B-Judge
yes	yes	yes	0.5031	0.5161	0.4888*	0.4745	0.4495	0.5471	0.4625	0.5202
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	0.4808*	0.4698	0.4599	0.5499	0.4638	0.5170
no	yes	yes	0.4998*	0.5301**	0.4731*	0.4856**	0.4421	0.5618	0.4383	0.5171
yes	no	no	0.4932	0.4984	0.4735^*	0.4519	0.4208	0.5083	0.4326	0.4638
no	yes	no	0.4931	0.5084*	0.4654*	0.4634*	0.4085	0.5134	0.3945	0.4554
no	no	yes	0.4979*	0.5277**	0.4673*	0.4829**	0.4407	0.5603	0.4391	0.5127
no	no	no#	0.4711	0.4884	0.4436	0.4448	0.4009	0.5069	0.3884	0.4469

(b) Comparison when using the shortest terms method

		Formal run						Prelimii	nary run	
Nu	nerical terms R-			R-Precision Average 1			R-Pre	ecision	Average precision	
$K_{location}$	$K_{category}$	K_{detail}	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	0.4546	0.5151
yes	yes	no	0.4867	0.4976	0.4704*	0.4464	0.4126	0.5136	0.4220	0.4649
yes	no	yes	0.5017	0.5094	0.4850*	0.4740	0.4410	0.5517	0.4556	0.5094
no	yes	yes	0.4991	0.5264**	0.4759*	0.4841**	0.4213	0.5616	0.4340	0.5095
yes	no	no	0.4883	0.4952	0.4647*	0.4444	0.4247	0.5076	0.4200	0.4614
no	yes	no	0.4824*	0.4990*	0.4537	0.4509	0.3927	0.5119	0.3901	0.4517
no	no	yes	0.4970	0.5242**	0.4693*	0.4804*	0.4198	0.5595	0.4332	0.5070
no	no	no#	0.4744	0.4897	0.4488	0.4487	0.3900	0.5082	0.3850	0.4468

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

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_{detail} and K_{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_{nado} , K_{num} , K_{hira} ,

Table 4: Comparison of detailed numerical terms

		Form	al run			Prelimir	nary run	
	R-Pre	ecision	Average	precision	R-Pre	cision	Average precision	
Detail terms	A-Judge	B-Judge	A-Judge	B-Judge	A-Judge	B-Judge	A-Judge	B-Judge
Neither#	0.4744	0.4897	0.4488	0.4487	0.3900	0.5082	0.3850	0.4468
K_{descr} only	0.4878	0.5125**	0.4614^*	0.4674^{**}	0.4136	0.5336	0.3930	0.4635
K_{proper} only	0.4746	0.4940	0.4481	0.4523	0.4031	0.5330	0.4172	0.4765
K_{nado} only	0.4630	0.4765	0.4384	0.4303	0.3973	0.5097	0.3859	0.4487
K_{num} only	0.4744	0.4897	0.4488	0.4487	0.3900	0.5082	0.3847	0.4465
K_{hira} only	0.4744	0.4897	0.4488	0.4487	0.3942	0.5074	0.3854	0.4470
K_{neg} only	0.4874	0.5037^*	0.4603	0.4628^*	0.4019	0.5134	0.3967	0.4554
$K_{stopword}$ only	0.4713	0.4941	0.4507	0.4548^{**}	0.3968	0.5295	0.3985	0.4629
K_{length} only	0.4775	0.4880	0.4472	0.4492	0.3945	0.5038	0.3809	0.4448

and $K_{stopword}$ did not improve precision, while K_{descr} and K_{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 0.4827, 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].

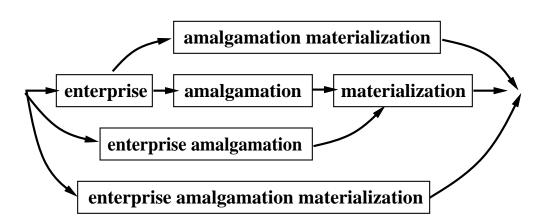
Acknowledgments

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Japanese Probabilistic Information Retrieval Using Location and Category Information

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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 [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 model². We verified the effectiveness of using

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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 [3]. 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> 企業合併</DESCRIPTION>
<NARRATIVE> 記事には企業合併成立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認定できる事。また、合併企業の分野、目的など具体的内容のいずれかが認定できる事。企業合併は企業併合、企業統合、企業買収も含む。</NARRATIVE>
</TOPIC>

English translation

tion in addition to Robertson's probabilistic information retrieval method.

¹A-judgment means that a document whose topic is relevant to a query is judged a relevant document.

²The reason that this paper is entitled "Probabilistic Information Retrieval Using Location Information and Category Information" is that our methods use location and category informa-

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

The condition for a relevent 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. </NARRATIVE> </TOPIC>

The number indicated by <TOPIC-ID> means the ID number of the query. CRIPTION> contains a phrase that indicates the information needed. <NARRATIVE> contains the sentences that restrict the information requested. During the task, the system receives a query such as the above one and outputs 300 documents in order of confidence.

Example of a Japanese document

<DOCNO>950217091</DOCNO> <SECTION>経済</SECTION> <HEADLINE>キグナス石油精製を東燃が100%子会社 化</HEADLINE> 東燃は十六日、系列のキグナス石油精製(資本金十億

円、本社・川崎市、森利英社長)を一〇〇%子会社化すると発表した。同社は東燃が七割、ニチモウが三割出資 しており、東燃はニチモウが所有する全株式六十万株を 百二十五億円で買収する。

</TEXT> </DOC>

English translation

<D0CN0>950217091</D0CN0> <SECTION>Economic page</SECTION> <HEADLINE>Tounen company completely makes Kigunasu company a subsidiary company </HEADLINE>

<TEXT> Tounen company anounced that it makes Kigunasu comapry, one of its group companies, (The capital is one billion yen. The head office is in Kawasaki city. The president is Mr. Toshihide Mori.) a completely subsidiary company. Kigunasu company is invested 70% by Tounen company and 30% by Nichimou company, and Tounen company purchases 600,000 stocks which Nichimou company possesses at 12,500,000,000 yens.

</TEXT> </DOC>

In this document, the newspaper information category (the economic or political pages) is indicated by SECTION>, the title of the document is indicated by <HEADLINE>, and the body of the document is indicated by <TEXT>. The tool "trec_eval" of TREC is used to evaluate the retrieval results [12]. In the contest, "R-Precision" were used. It indicates the precision when retrieving R documents, where R is the number of relevant documents.

Outline of our method 2.2

Our information retrieval method uses Robertson's 2poisson model [8] which is one kind of probabilistic approach. Robertson's method calculates each document's score using the following equation³, 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.)

$$Score(d,q) = \sum_{\substack{\text{term } t \\ \text{in } q}} \left(\frac{tf(d,t)}{tf(d,t) + k_t \frac{length(d)}{\Delta}} \times \log \frac{N}{df(t)} \right) \times \frac{tf_q(q,t)}{tf_q(q,t) + kq}$$

$$(1)$$

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

by experiments. In this equation, we call $\frac{tf(d,t)}{tf(d,t)+k_t}\frac{tength(d)}{\Delta}$ the TF term, (abbr. TF(d,t)), $\log\frac{N}{df(t)}$ the IDF term, (abbr. IDF(t)), and $\frac{tf_q(q,t)}{tf_q(q,t)+k_q}$ the TF $_q$ term, (abbr. $TF_q(q,t)$).

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

$$Score(d.q) = K_{category}(d) \begin{cases} \sum_{\substack{\text{term } t \\ \text{in } q}} (TF(d,t) \times IDF(t)) \\ \times TF_{q}(q,t) \times K_{detail}(d,t) \times K_{location}(d,t)) \\ + \frac{length(d)}{length(d) + \Delta} \end{cases}$$
(2)

The TF, IDF and TF_q terms in this equation are identical to those in Eq. (1). The term $\frac{length}{length+\Delta}$ 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 文書 "document" and \mathfrak{to} "thing". In the next section, we explain these extended numerical terms in detail.

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.

³This equation is BM11, which corresponds to BM25 in the case of b = 1[9]. 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 $(K_{location})$

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 $K_{location}$ 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:

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

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 a economic page and decrease the score of the document whose page is different. $K_{category}$ is expressed as follows;

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

where RatioA is the ratio of a category in the top 100 documents of the first retrieval. RatioB is the ratio of a category in all the documents. The value of $K_{category}(d)$ is large, when RatioA is large (page of a document d occurs frequently in the top 100 documents of the first retrieval.) and 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 文書 "document" and \mathfrak{to} "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 \mathfrak{to} "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:

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

Each term in this equation is explained below.

\bullet 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.

\bullet 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.

\bullet 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.

\bullet 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.

\bullet 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.

\bullet 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> 国連軍の派遣</DESCRIPTION> <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る事。</NEG> 日本の自衛隊を国 連に派遣するかどうかという問題のみに関する記事は除く。</NEG></NARRATIVE> </TOPIC>

English translation

<TOPIC>

<TOPIC-ID>1003</TOPIC-ID>
<DESCRIPTION>Dispatch of the United
Nations forces</DESCRIPTION>
<NARRATIVE>The condition for a
relevent document is that in the
document a dispatch of the United
Nations forces in the activity of UN
such as peace maintainence 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 elimated.

</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 baai (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" [2] and eliminates non-nominal words and stop words⁴. 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" 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 $\sqrt{\frac{n(n+1)}{2}}$, 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

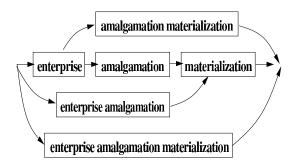


Figure 1: An example of a lattice structure

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 the weight of the longer terms. We decided to multiply the weight $k_{down}^{\ x-1}$ to a term, when it consisted of x shortest 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 contest⁶, we selected the "all-term patterns" and "lattice structure" methods to extract terms⁷, 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; $k_{location,1} = 1.35, k_{location,2} = 0.125, k_{category} = 0, k_{descr} = 1.5, k_{proper} = 2, k_{nado} = 1, k_{num} = 0.5, k_{hira} = 0.5, k_{neg} = 0, k_{stopword,1} = 0, k_{stopword,2} = 0.5, k_t = 1,$

⁴Since, Japanese is an agglutinative languages like Chinese, there are no spaces between words and a morphological analyzer is processor; to divide a centence into words

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 readers. 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 "downweighting method" is a method proposed at IREX. So we could not use it in IREX.

Table 1: R-Precision of all the systems

System ID	A-Judgment	B-Judgment
1103a	0.4505	0.4888
1103b	0.4657	0.5201
1106	0.2360	0.2120
1110	0.3329	0.4276
1112	0.2790	0.3343
1120	0.2713	0.3339
1122a	0.3808	0.4689
1122b	0.4034	0.4747
1126	0.0966	0.0891
1128a	0.3384	0.3897
1128b	0.3924	0.4175
1132	0.0602	0.0791
1133a	0.2383	0.2277
1133b	0.2457	0.2248
1135a	0.4926	0.5119
1135b	0.4827	0.4878
1142	0.4455	0.4929
1144a	0.4658	0.5510
1144b	0.4592	0.5442
1145a	0.3352	0.3424
1145b	0.2553	0.2935
1146	0.2220	0.2742

and $k_q=0.1$. 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; $k_{location,1} = 1.3$, $k_{location,2} = 0.15$, $k_{category} = 0.1$, $k_{descr} = 1.75$, $k_{proper} = 2$, $k_{nado} = 1.7$, $k_{num} = 0.5$, $k_{hira} = 0.5$, $k_{neg} = 0$, $k_{stopword,1} = 0$, $k_{stopword,2} = 0.5$, $k_t = 1$, and $k_q = 0$. Terms obtained from DE-SCRIPTION 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-Judgement 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 $k_{down} = 0.1$ 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 $K_{length} = \frac{length}{length + \Delta}$ 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

(-y · ·										
		Form			Preliminary run					
Method to extract terms	R-Pre	R-Precision		Average precision		R-Precision		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**	0.4935**	0.4764*	0.4412	0.5442	0.4546	0.5151		
Using all term patterns#	0.4827	0.4878	0.4553	0.4453	0.4373	0.5573	0.4576	0.5317		
Using the lattice structure	0.4926	0.5119	0.4808	0.4698	0.4599	0.5499	0.4638	0.5170		
Using down-weight $(k_{down} = 0.01)$	0.5006	0.5217	0.4935	0.4778	0.4412	0.5445	0.4546	0.5157		
Using down-weight $(k_{down} = 0.1)$	0.4997	0.5233	0.4939	0.4809	0.4478	0.5504	0.4563	0.5185		

(b) When no extended terms are used

		Form	al run		Preliminary run				
Method to extract terms	R-Pre	cision	Average	Average precision		cision	Average precision		
	A-Judge	B-Judge	A-Judge	B-Judge	A-Judge	B-Judge	A-Judge	B-Judge	
Using the shortest terms	0.4744	0.4897	0.4488*	0.4487*	0.3900	0.5082	0.3850	0.4468	
Using all term patterns#	0.4445	0.4665	0.4172	0.4180	0.3965	0.4981	0.3960	0.4444	
Using the lattice structure	0.4711	0.4884	0.4436	0.4448	0.4009	0.5069	0.3884	0.4469	
Using down-weight $(k_{down} = 0.01)$	0.4760	0.4896	0.4492	0.4494	0.3940	0.5082	0.3850	0.4470	
Using down-weight $(k_{down} = 0.1)$	0.4816	0.4986	0.4545	0.4568	0.4003	0.5076	0.3860	0.4498	

The method tagged with "#" is a base method for comparison. A result tagged with "*" is superior to the base method's 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

(a) comparison when using the lattice method												
				Form	al run			Prelimi	nary run			
Numerical terms R-Precision			cision	ision Average precision			cision	Average precision				
$K_{location} K_{category} K_{detail}$		K_{detail}	A-Judge	B-Judge	A-Judge	B-Judge	A-Judge	B-Judge	A-Judge	B-Judge		
yes	yes	yes	0.5031	0.5161	0.4888*	0.4745	0.4495	0.5471	0.4625	0.5202		
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	0.4808*	0.4698	0.4599	0 . 5499	0.4638	0.5170		
no	yes	yes	0.4998*	0.5301**	0.4731*	0.4856**	0.4421	0.5618	0.4383	0.5171		
yes	no	no	0.4932	0.4984	0.4735*	0.4519	0.4208	0.5083	0.4326	0.4638		
no	yes	no	0.4931	0.5084*	0.4654*	0.4634*	0.4085	0.5134	0.3945	0.4554		
no	no	yes	0.4979*	0.5277**	0.4673*	0.4829**	0.4407	0.5603	0.4391	0.5127		
no	no	no#	0.4711	0.4884	0.4436	0.4448	0.4009	0.5069	0.3884	0.4469		

(b) Comparison when using the shortest terms method

	Formal run						Preliminary run				
Nur	Numerical terms			R-Precision		Average precision		cision	Average	precision	
$K_{location}$	$K_{category}$	K_{detail}	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	0.4546	0.5151	
yes	yes	no	0.4867	0.4976	0.4704*	0.4464	0.4126	0.5136	0.4220	0.4649	
yes	no	yes	0.5017	0.5094	0.4850*	0.4740	0.4410	0.5517	0.4556	0.5094	
no	yes	yes	0.4991	0.5264**	0.4759*	0.4841**	0.4213	0.5616	0.4340	0.5095	
yes	no	no	0.4883	0.4952	0.4647*	0.4444	0.4247	0.5076	0.4200	0.4614	
no	yes	no	0.4824*	0.4990*	0.4537	0.4509	0.3927	0.5119	0.3901	0.4517	
no	no	yes	0.4970	0.5242**	0.4693*	0.4804*	0.4198	0.5595	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 0.027 to 0.045 when our extended terms were used. (For example, the average precision of A-Judgement of the shortest terms method improved from 0.4488 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 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.

Table 4: Comparison of detailed numerical terms

Table 1. Companion of accance name terms											
		Form	al run			$\operatorname{Prelimin}$	nary run				
	R-Pre	cision	Average	precision	R-Pre	cision	Average precision				
Detail terms	A-Judge	B-Judge	A-Judge	B-Judge	A-Judge	B-Judge	A-Judge	B-Judge			
Neither#	0.4744	0.4897	0.4488	0.4487	0.3900	0.5082	0.3850	0.4468			
K_{descr} only	0.4878	0.5125**	0.4614*	0.4674**	0.4136	0.5336	0.3930	0.4635			
K_{proper} only	0.4746	0.4940	0.4481	0.4523	0.4031	0.5330	0.4172	0.4765			
K_{nado} only	0.4630	0.4765	0.4384	0.4303	0.3973	0.5097	0.3859	0.4487			
K_{num} only	0.4744	0.4897	0.4488	0.4487	0.3900	0.5082	0.3847	0.4465			
K_{hira} only	0.4744	0.4897	0.4488	0.4487	0.3942	0.5074	0.3854	0.4470			
K_{neg} only	0.4874	0.5037^*	0.4603	0.4628*	0.4019	0.5134	0.3967	0.4554			
$K_{stopword}$ only	0.4713	0.4941	0.4507	0.4548**	0.3968	0.5295	0.3985	0.4629			
K_{length} only	0.4775	0.4880	0.4472	0.4492	0.3945	0.5038	0.3809	0.4448			

4.3 Effectiveness of detail terms

This section examines the effectiveness of the terms of K_{detail} and K_{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_{nado} , K_{num} , K_{hira} , and $K_{stopword}$ did not improve precision, while K_{descr} and K_{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 0.4827, 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].

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