# A Novelty-based Evaluation Method for Information Retrieval

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#### Abstract

In information retrieval research, precision and recall have long been used to evaluate IR systems. However, given that a number of retrieval systems resembling one another are already available to the public, it is valuable to retrieve novel relevant documents, i.e., documents that cannot be retrieved by those existing systems. In view of this problem, we propose an evaluation method that favors systems retrieving as many novel documents as possible. We also used our method to evaluate systems that participated in the IREX workshop.

#### 1. Introduction

In information retrieval (IR) research, the notion of precision and recall have commonly been used to evaluate the empirical performance of systems (Keen, 1992; Salton, 1992). Precision is the ratio of the number of relevant documents retrieved by a system under evaluation, compared to the total number of documents retrieved by the system. On the other hand, recall is the ratio of the number of relevant documents retrieved by the system, compared to the total relevant documents in a given benchmark test collection.

In other words, the precision/recall-based evaluation method regards all the relevant documents as equally important or informative for the user, and thus highly values systems that retrieve as many relevant documents as possible, with little noise.

However, in the real world, where a number of IR systems are available, for example, on the World Wide Web, it is often the case that the user has already read some of relevant documents using other systems. Thus, systems that always retrieve relevant documents similar to those retrieved by ubiquitous systems have little practical utility. In addition, meta search systems, which integrate document sets retrieved by more than one system, are less effective, in the case where individual systems retrieve similar documents.

In view of these problems, our proposed IR evaluation method favors systems that retrieve more *novel* documents, that is, relevant documents which cannot be retrieved by other existing systems.

From a different perspective, our evaluation method is also effective in producing test collections. The pooling method (Voorhees, 1998), which has commonly been used to produce test collections, requires a variety of participating systems. However, in the case where most participating systems adopt similar techniques, it is not feasible to collect a sufficient "pool" (i.e., a set of candidates for relevant documents). Our evaluation method is expected to promote a development of IR systems with various concepts, and therefore resolve the above problem.

Section 2. formalizes the evaluation measure based on the novelty of documents, and Section 3. applies this measure to evaluate IR systems that participated in the IREX workshop (Sekine and Isahara, 1999).

#### 2. Formalizing the Measure

Instead of the notion of precision and recall, we propose as a new evaluation measure the utility of system x with respect to relevant document d,  $U_d(x)$ . This measure denotes the extent to which x contributes to providing the user with d, for a given query. Note that in this paper, d generally refers to a *relevant* document.

From an information theoretical point of view, we calculate  $U_d(x)$  as the ratio of the probability that the user reads document d by using system x, P(D = d|S = x), compared to the probability that the user reads d by using another system (i.e., even without using x), P(D = d), as shown in Equation (1).

$$U_d(x) = \log \frac{P(D=d|S=x)}{P(D=d)}$$
(1)

In the case where system x adopts a ubiquitous retrieval technique, the value of P(D = d|S = x) becomes similar to that of P(D = d), and thus the utility of x becomes small. On the other hand, the utility of x becomes greater as the number of *novel* relevant documents provided by x increases.

We then calculate the *total* utility of x, U(x), by summing up  $U_d(x)$ 's of all the relevant documents for the query, as shown in Equation (2).

$$U(x) = \sum_{d} U_d(x) \tag{2}$$

To sum up, our evaluation method favors systems with greater U(x).

In Equation (1), P(D = d) is the summation of P(D = d|S = y)'s for existing systems, averaged by the probability that the user utilizes system y, P(S = y). Thus, given a set of existing system excluding x, E, we calculate P(D = d) as in Equation (3).

$$P(D = d) = \sum_{y \in E} P(D = d | S = y) \cdot P(S = y)$$

$$\approx \sum_{y \in E} P(D = d | S = y) \cdot \frac{1}{|E|}$$
(3)

Here, note that we assume uniformity with respect to P(S = y).

Finally, the crucial content is the way to estimate P(D = d|S = x), i.e., the probability that the user reads document d by using system x. It can safely be assumed that the user always reads the top document,  $d_1$ , and thus  $P(D = d_1|S = x)$  always takes 1. However, the probability that the user reads remaining documents becomes smaller according to their ranking.

Given N documents sorted according to their relevance degree, in descending order, the user can choose a threshold for the ranking (i.e., the boundary until which he/she continues to read) out of N choices. Consequently, documents ranked lower than the threshold will be discarded.

In other words, we can calculate P(D = d|S = x) as the probability that the user chooses a threshold equal to or greater than the ranking of d, as in Equation (4).

$$P(D = d | S = x) = \sum_{i=r_{x,d}}^{N} \frac{1}{N}$$

$$= \frac{N - r_{x,d} + 1}{N}$$
(4)

Here,  $r_{x,d}$  is the ranking of document d determined by system x.

# 3. A Case Study using the IREX Collection

Our concern in this section is to investigate the characteristic of our evaluation method. For this purpose, we targeted IR systems participated in the IREX workshop (Sekine and Isahara, 1999), and compared the result obtained based on our newly proposed evaluation method, with that based on the precision/recall. We also investigated reasons behind the difference between those two results, if any.

#### 3.1. Overview of the IREX Collection

The IREX collection was produced through the IREX workshop (Sekine and Isahara, 1999), which consists of TREC-style IR and MUC-style named entity (NE) tasks for Japanese.<sup>1</sup> Hereafter, the IREX collection/workshop refers solely to that related to the IR task.

The IREX collection consists of 30 queries, 211,853 articles collected from two years worth of "Mainichi Shimbun" newspaper articles (Mainichi Shimbun, 1994-1995),<sup>2</sup> relevance assessment for each query, retrieval results of 22 participating systems, and technical details of each system.

Each query consists of the ID, description and narrative. While descriptions are usually phrases to

briefly express the topic, narratives consist of several sentences and synonyms associated with the topic. Figure 1 shows an example query in the SGML form (translated into English by one of the organizers of the IREX workshop).

```
<TOPIC>
<TOPIC-ID>1001</TOPIC-ID>
<DESCRIPTION>Corporate
merging</DESCRIPTION>
<NARRATIVE>The article describes a
corporate merging and in the article, the
name of companies have to be
identifiable. Information including the
field and the purpose of the merging have
to be identifiable. Corporate merging
includes corporate acquisition, corporate
unifications and corporate
buying.</NARRATIVE>
</TOPIC>
```

Figure 1: An example query in the IREX collection.

Relevance assessment was performed based on the pooling method (Voorhees, 1998). That is, candidates for relevant documents were first pooled using the 22 participating systems. Thereafter, for each candidate document, human experts assigned one of three ranks of relevance, i.e., "relevant", "partially relevant" and "irrelevant". The average number of documents pooled for each query is 2,105, among which the number of relevant and partially relevant documents are 68 and 116, respectively.

Each retrieval result consists of the top 300 articles submitted in the same form as used in the TREC.<sup>3</sup> For each of the 22 results, the TREC evaluation software was used to investigate the performance (e.g., 11-point non-interpolated average precision). Figure 2 shows a fragment of the retrieval result obtained with one of the participating systems, which consists of the query ID, dummy field, article ID, ranking of the article, relevance degree computed by the system, and system ID.

1007	0	940228106	1	0.306856	1106
1007	0	940110130	2	0.246505	1106
1007	0	950106119	3	0.237173	1106
1007	0	940131126	4	0.236115	1106
1007	0	940614009	5	0.223313	1106
1007	0	940614002	6	0.222998	1106
1007	0	941107114	7	0.217324	1106
1007	0	940428222	8	0.215979	1106

Figure 2: A fragment of the retrieval result of system "1106".

It should be noted that using relevance assessment

<sup>&</sup>lt;sup>1</sup>http://cs.nyu.edu/cs/projects/proteus/irex/ index-e.html

<sup>&</sup>lt;sup>2</sup>Practically speaking, the IREX collection provides only article IDs, which corresponds to articles in Mainichi Shimbun newspaper CD-ROM'94-'95. Participants must get a copy of the CD-ROMs themselves.

<sup>&</sup>lt;sup>3</sup>http://trec.nist.gov/pubs.html

Question	Answers							
query information used	only description (8), description+narrative (14)							
indexing method	word (9), n-gram (3), word+character (2), character (1), syntactic phrase (1),							
	statistical phrase (1)							
proper noun identification	yes(5)							
query expansion	local feedback $(2)$ , use of a thesaurus $(2)$							
retrieval method	vector space model (13), probabilistic model (4), latent semantic indexing (1)							

Table 1: A fragment of the result of the IREX questionnaire.

and retrieval results for each system, we can easily calculate P(D = d|S = x) in Equation (4), which is the central issue in estimating our evaluation measure.

Technical details of participating systems were collected from questionnaires answered by each participant, where questions ranged from retrieval algorithms used to execution time. Although several questions are relatively vague, a number of questions are effective to characterize each system.

Table 1 shows representative questions in terms of retrieval accuracy. In this table, the number of answers are indicated in parentheses. However, answers classified as "no", "unknown" and "etc." are not shown. Roughly speaking, most systems adopted the wordbased indexing and vector space model combined with TF·IDF term weighting.

On the other hand, note that in the IREX workshop, the correspondence between system IDs and participants is not available to the public. Additionally, several participants did not have oral presentations and papers in the proceedings. Consequently, for some systems it is difficult to obtain sufficient technical details.

For example, although most participants answered "TF·IDF" for the question about term weighting method, it is not possible to identify the exact formula used, out of a number of variants (Salton and Buckley, 1988; Zobel and Moffat, 1998), for several systems.

#### 3.2. Experimentation

As explained in Section 3.1., the 22 IREX participating systems have already been ranked based on the conventional precision/recall, using the TREC evaluation software.

Thus, we re-evaluated the 22 systems based on our evaluation method, and compared results derived from different evaluation methods. To put it more precisely, we conducted 22 trials in each of which a different system was under evaluation and the rest were regarded as existing systems. That is, the former and latter correspond to x and E in Section 2., respectively.

Note that in this evaluation, we did not regard "partially relevant" documents as relevant ones, because interpretation of "partially relevant" is not fully clear to the authors.

Table 2 compares rankings obtained based on 11point non-interpolated average precision and the utility factor we proposed in this paper. Table 3 compares rankings obtained with two evaluation methods on a query-by-query basis, where we show solely the difference of rankings for enhanced readability. Since in the IREX collection, every query ID consists of four digits stating with "10", we simply show the remaining two digits in Table 3.

System ID	Avg. Precision	Utility	Difference
1144b	2	1	+1
1135a	3	2	+1
1144a	1	3	-2
$1135\mathrm{b}$	4	4	0
1103b	5	5	0
1106	17	6	+11
$1145\mathrm{b}$	16	7	+9
1122b	7	8	-1
1103a	10	9	+1
1128b	9	10	-1
1142	6	11	-5
1122a	8	12	-4
1110	11	13	-2
1133a	19	14	+5
1133b	18	15	+3
1128a	12	16	-4
1120	14	17	-3
1145a	13	18	-5
1112	15	19	-4
1146	20	20	0
1132	22	21	+1
1126	21	22	-1

Table 2: Comparison of rankings obtained based on 11-point non-interpolated average precision and utility factor.

#### 3.3. Discussion

Looking at Table 2, one may notice that rankings of systems "1106", "1145b", "1133a" and "1133b" were significantly improved within our evaluation method. Thus, we investigated properties that characterize each of those four systems, in a comparison with other systems.

First, we found that "1106" adopted a relatively simple implementation, while most systems used more elaborate ones. To put it more precisely, morphological analysis was performed, and nouns/verbs were extracted for a word-based indexing. For term weighting, a TF·IDF formula as in Equation (5) was used, while most systems used different methods, such as the log-

														Qu	iery	ID														
System ID	07	08	09	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
1103a	8	-7	14	0	8	3	3	-14	1	13	5	-3	0	-4	-2	3	-6	-3	6	1	-2	13	$^{2}$	14	-3	-5	-7	-2	-3	3
$1103 \mathrm{b}$	-2	-5	6	4	- 1	-3	-6	-9	4	-5	- 1	1	-3	-2	- 1	8	0	-2	1	-2	-1	7	1	-3	-5	- 1	-6	-3	-2	5
1106	8	-4	-9	-2	9	-2	7	11	5	-1	-2	-4	5	4	0	-3	-3	$^{2}$	0	0	-1	-1	1	$^{2}$	1	$^{2}$	0	$^{2}$	17	0
1110	6	-1	-4	4	- 1	9	-4	-10	-1	0	4	-2	-5	-1	0	3	0	-2	-1	0	0	16	13	- 1	-3	-3	8	1	3	-2
1112	-2	-5	0	0	-5	3	-3	1	-11	0	5	-5	12	-2	- 1	5	-3	-4	-3	- 1	-1	-4	-6	-4	3	1	-4	-2	0	0
1120	1	-2	-2	- 1	0	-3	4	-8	- 1	0	5	-2	$\overline{7}$	1	0	5	0	$^{2}$	0	$^{2}$	0	-3	- 1	- 1	$^{2}$	$^{2}$	6	5	- 1	0
1122a	-2	$^{2}$	-2	-7	-5	5	-5	-11	-1	-5	1	8	- 1	-6	-2	-8	1	1	0	- 1	4	-4	1	- 1	-3	- 1	3	-2	-3	- 1
$1122 \mathrm{b}$	-5	0	-8	1	0	-8	1	-5	-9	-5	0	-2	-3	-6	1	-4	4	0	-2	1	7	-3	-2	-4	-4	0	6	0	-1	-2
1126	0	4	-10	0	0	-2	0	3	- 1	- 1	- 1	1	- 1	0	0	0	0	0	0	1	1	0	-2	-3	0	0	-3	-1	0	0
1128a	- 1	- 1	4	-2	-3	0	3	-6	-8	- 1	-3	4	$^{2}$	9	1	-13	0	6	$^{2}$	- 1	0	-2	1	0	- 1	1	4	-4	0	4
$1128 \mathrm{b}$	-2	14	-4	-4	-7	- 5	11	9	-2	-2	-5	4	- 1	3	-2	-13	- 1	1	$^{2}$	$^{2}$	0	1	0	- 5	1	- 1	0	-4	0	- 1
1132	0	16	-9	$^{2}$	0	0	0	12	21	0	0	10	0	8	15	0	-4	0	0	0	0	0	$^{2}$	0	0	- 1	0	13	0	0
1133a	-2	-2	-4	0	3	$^{2}$	3	15	11	1	-5	-1	1	7	-1	3	4	1	4	1	0	-2	- 1	1	4	7	-1	0	0	1
$1133 \mathrm{b}$	-3	-2	-4	$^{2}$	3	1	11	15	3	0	-4	$^{2}$	0	5	1	6	5	0	3	1	0	-3	-5	-1	10	3	-2	-2	1	- 1
1135a	- 1	-2	9	-2	4	-11	-6	4	9	$^{2}$	-6	-4	- 1	-1	- 1	-2	-3	-1	-1	- 1	0	-2	-2	0	1	- 1	-1	0	- 1	-3
$1135\mathrm{b}$	$^{2}$	0	6	-1	-12	-13	-6	1	$^{2}$	0	-3	1	-5	-6	-3	-1	-3	-2	0	-1	-4	-7	-2	0	0	-2	-1	-7	-2	0
1142	-4	- 1	10	0	- 5	- 1	-7	-14	-7	-3	-2	-3	-4	-7	-5	-2	4	-3	-3	- 1	-2	-2	-2	- 5	$^{2}$	-6	-7	-6	- 1	-4
1144a	-2	- 1	- 1	3	- 1	5	-16	-9	-3	5	1	-6	- 1	-2	0	6	- 1	-2	-2	-3	0	0	-2	-1	0	-4	7	$^{2}$	- 1	- 1
1144b	-2	3	- 1	$^{2}$	-2	5	-16	-5	-2	5	$^{2}$	-5	$^{2}$	-2	1	5	- 3	1	1	- 1	0	0	-5	-2	0	1	4	$^{2}$	-1	$^{2}$
1145a	0	-4	-7	-4	-5	- 1	5	11	-2	- 1	- 1	-3	- 1	-1	- 1	1	8	-3	-5	5	-1	-4	5	6	-2	$^{2}$	-4	-3	1	-3
$1145\mathrm{b}$	3	- 3	-5	5	13	7	12	13	- 5	- 1	-2	8	-3	4	0	2	1	1	-2	0	-1	0	5	6	-2	7	0	13	-5	0
1146	0	1	21	0	7	9	9	-4	- 3	-1	12	1	0	-1	0	-1	0	7	0	-2	1	0	-1	$^{2}$	- 1	-1	-2	-2	- 1	3

Table 3: Query-by-query comparison of rankings obtained based on 11-point non-interpolated average precision and utility factor.

arithmic TF formulation as in Equation (6) and one proposed by Robertson and Walker (1994).

$$f_{t,d} \cdot \log \frac{N}{n_t} \tag{5}$$

$$(1 + \log f_{t,d}) \cdot \log \frac{N}{n_t} \tag{6}$$

Here,  $f_{t,d}$  denotes the frequency that term t appears in document d, and  $n_t$  denotes the number of documents containing term t. N is the total number of documents in the collection.

Second, "1145b" conducted a query expansion (Qiu and Frei, 1993), while a few systems used query expansion (e.g., one based on a thesaurus). In addition, a term weighing method based on mutual information between two terms was introduced. Possible rationales behind this method include that two terms frequently co-occur are effective to characterize the domain of documents, and are thus assigned with greater term weights.

Third, "1133a" and "1133b" also used domain knowledge for term weighting. However, unlike the case of "1145b", they regarded pages of news articles as domain. In practice, a greater weight is assigned to terms whose distribution varies more strongly depending on the page, because they are expected to characterize the domain. On the other hand, terms commonly appear in more pages are assigned with a lesser weight.

To sum up, our novelty-based evaluation revealed the effectiveness of those properties above, specifically term weighting methods introduced in "1145b", "1133a" and "1133b", which were overshadowed or underestimated within the precision/recall-based evaluation.

We devote a little space to consider Table 3 for further investigation. We arbitrarily regarded improvements above seven as significant, and focused solely on systems with relatively many significant improvements, that is, "1103a" and "1132". Although "1145b" is associated with the same number of significant improvements as "1132", we previously discussed system "1145b" above.

We found that "1103a" is one of five systems that conducts a proper noun identification, and that five of six queries where "1103a" achieved significant improvements are directly or indirectly associated with proper nouns.

Samples of query descriptions directly and indirectly related to proper nouns include "1016: Nick Price (a golfer)" and "1011: arrest of suspects of robbery in the *Kanto* region", respectively. Note that in the latter (indirect) case, Japanese prefectures within the "*Kanto*" region, which are not explicitly described in the query (e.g., "*Tokyo*" and "*Kanagawa*"), must be identified in news articles.

Finally, "1132" is the only system that used Latent Semantic Indexing (LSI), which is an extension of the vector space model, so as to retrieve relevant documents including no common terms in a given query. While as shown in Table 2, "1132" had the lowest ranking in terms of the average precision, our evaluation method indicated that in many cases (queries) an LSI-based method is expected to retrieve relevant documents that other types of methods fail to retrieve.

### 4. Conclusion

Evaluation methods based on precision and recall have long been used in information retrieval (IR) research, where systems that retrieve as many relevant documents as possible are usually highly valued.

However, given the fact that a number of retrieval systems resembling one another are available to the public (not only in laboratories), it is valuable to retrieve relevant documents that can never be retrieved by those existing systems. This notion is also true in various contexts that require a variety of IR systems, such as meta search systems and the pooling method in producing IR test collections.

In consideration of these factors, we proposed a new evaluation method for IR, which favors systems that retrieve more novel documents, i.e., relevant documents that many systems fail to retrieve. To realize this notion, we estimated the utility of a system in question by comparing the probability that the user reads relevant documents by using the system, and the probability that the user can read those documents even without using the system.

We also applied our evaluation method to the 22 systems that participated in the IREX workshop, and identified several effective techniques that have been underestimated in the conventional precision/recall-based evaluation method.

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