Sensitivity of IR systems Evaluation to Topic Difficulty

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Abstract
The difficulty of the topics or queries is one of important factors in evaluating information retrieval (IR) systems. This paper analyzes the differences of system ranking affected by the topic difficulty using a test collection ‘NTCIR-1,’ which is constructed for evaluating Japanese IR systems and composed of (1) the topics, (2) the document database, and (3) the lists of relevant judgments. Furthermore, this paper defines measures for the various features on the topics, and analyzes the correlation between them, in order to investigate the predictability of the topic difficulty.

1. Introduction

The ’NTCIR’ workshop is one of the evaluation workshops for information retrieval (IR) systems and compares the retrieval effectiveness of each system using a common test collection (National Institute of Informatics, 2001). Here, a test collection means a benchmark set for the experiments on IR systems, and is composed of (1) the document database, (2) the topics, and (3) the list of relevant judgments for each topic.

The topics are to be balanced for topic difficulty. The topic difficulty distribution should not be biased, as it is neither too difficult nor too easy, in order to keep reliability of test collections. This paper investigates the properties of topics in a test collection and the sensitivity of IR systems evaluation to the topic difficulty. We defi netopic difficulty using a test collection ‘NTCIR-1’ (Kando et al., 1999), and analyses the differences of system ranking caused by the differences of the topic difficulty.

2. Defining Topic Difficulty and Measuring Topic Features

2.1. Definition of Actual Topic Difficulty

In order to identify the actual topic difficulty we categorized the topics on the basis of the median of non-interpolated average precision; this means retrieval effectiveness, and indicates the actual topic difficulty of the submitted result set for each topic.

We analyzed the test topics using only the 26 submitted result set of non-interactive searches, which were done, in the ad hoc IR task, by automatic query construction and by using only the descriptions of the topics1. This was to try to avoid the different retrieval effectiveness distributions that result when the query uses an interactive search or a non-interactive search using different parts of the topic. Then, we categorize the topics, ranked according to the medi ans in ascending order, into the following three categories: “hard,” “middle” and “easy,” so that each of the categories contains the same number of topics. This categorization is, in this paper, referred to as actual topic difficulty and indicated as \[diff\].

2.2. Function-based Topic Categorization

We use the function-based topic categorization as one measure of the human-judged topic difficulty.

According to the function-based topic categorization in BMIR-J2 (Sakai et al., 1999), we defi ne the following functions. Here, “the basic function” achieved by keyword search or query expansion using thesauri, as defi ned in BMIR-J2, is divided into “F0. basic function” and “F1. thesaurus function”.

F0. basic function: The relevant texts can be retrieved by simply using words extracted from the query, or by their Boolean expressions.

F1. thesaurus function: The relevant texts can be retrieved using words extracted from the query and their related words expanded by thesauri, or by satisfying their Boolean expression.

F2. numerical range function: The system needs to handle a numeric range description.

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1While the analysis of actual topic difficulty in this paper, we used only “relevant” judgments but not “partially relevant.”
Table 1: The results of the function-based topic categorization.

| the function-based topic categorization | F0 | F1 | F2 | F3 | F4 | F5 |
|----------------------------------------|----|----|----|----|----|----|
| A. basic function                      | 1  | 0  | 0  | 0  | 0  | 0  |
| B. thesaurus function                  | 1  | 1  | 0  | 0  | 0  | 0  |
| C. syntactic function                  | 1  | 0  | 0  | 1  | 0  | 0  |
| D. thesaurus function & syntactic function | 1  | 1  | 0  | 1  | 0  | 0  |
| E. thesaurus function & semantic function | 1  | 1  | 0  | 0  | 1  | 0  |
| F. thesaurus function, syntactic function | 1  | 1  | 0  | 1  | 1  | 0  |

F3. syntactic function: Analysing a syntactic relationship among query words helps the query be understood.

F4. semantic function: A semantic / context analysis is required to understand the query.

F5. the world knowledge function: Common sense / world knowledge is required to process the query. Such information is often missing in the text or the system’s lexicon.

Assessors, two graduate school students, performed the judgments for the function-based topic categorization. As the results of the judgments, the existence of each function is represented as “1” in Table 1.

In general, the effective search execution tends to be difficult in the order A, B, C, D, E and F, since the processing required increases in the same order. Thus, the function-based topic categorization can be used as one measure of the human-judged topic difficulty.

2.3. Feature Quantities of the Topics

We consider the nouns and compound words in the topic to be the topic terms that typically represent each topic. In order to extract topic terms, we perform a Japanese morphological analysis for each topic, and then obtain the compound words by applying some rules to the morpheme set.

Using them, we define the following features of the topics

- the frequencies of the topic terms in the document database,
- the frequencies of the documents that include the topic terms in the document database.
- the frequencies of the documents that include the topic terms in the document database.

The aforementioned term frequencies, the document frequencies and the combination between them are discussed in Subsecs. 2.3.1., 2.3.2. and 2.3.3.

2.3.1. Term Frequencies of The Topic Terms

We define the following \( tf_{\mathcal{A}} (tp) \) for the topic \( tp \). Here, \( TT \) indicates the topic term set which constitute the topic, and \( tm \) indicates the topic term that is an element of \( TT \). \( DB \) indicates the document database, while \( tf (tm, A) \) indicates the frequency of a term \( tm \) in the document set \( A \).

\[
 tf_{\mathcal{A}} (tp) = \frac{1}{|TT|} \sum_{tm \in TT} tf (tm, DB). \tag{1}
\]

2.3.2. Document Frequencies of the Topic Terms

We define the following \( df_{\mathcal{A}} (tp) \) for the topic \( tp \). Here, \( df (tm, A) \) indicates the frequency of a document that includes a term \( tm \) in the document set \( A \).

\[
 df_{\mathcal{A}} (tp) = \frac{1}{|TT|} \sum_{tm \in TT} df (tm, DB). \tag{2}
\]

2.3.3. TF-IDF

We apply the TF-IDF weighting method, which is a well-known result in IR research areas, to compute frequency-based feature quantities of the topics. We define the following \( tfidf_{\mathcal{A}} (tp) \) and \( ltfidf_{\mathcal{A}} (tp) \). The former is a naive TF-IDF method (Salton, 1989) and the latter is often used in IR systems based on a vector space model (Buckley et al., 1993).

\[
 tfidf_{\mathcal{A}} (tp) = \frac{1}{|TT|} \sum_{tm \in TT} tf (tm, DB) \cdot idf (tm, DB), \tag{3}
\]

\[
 ltfidf_{\mathcal{A}} (tp) = \frac{1}{|TT|} \sum_{tm \in TT} ltf (tm, DB) \cdot idf (tm, DB), \tag{4}
\]

\[
 ltf (tm, DB) = \frac{1}{|TT|} \sum_{tm \in TT} ltf (tm, DB), \tag{5}
\]

\[
 idf (tm, DB) = \log(N/idf (tm, A)), \tag{6}
\]

where

\[
 ltf (tm, A) = \log(tf (tm, A)) + 1, \tag{7}
\]

\[
 idf (tm, A) = \log(N/idf (tm, A)). \tag{8}
\]

3. Results

3.1. System Ranking Comparison for Different Topic Difficulty Levels

We analyze the differences of system ranking caused by the topic difficulty since we consider that the system ranking might be affected by the topic difficulty for example,
one system is good at retrieval for average levels of topic diffi culty but bad at retrieval for diffi cult topics, and another is conversely good at retrieval for a kind of diffi cult topics.

At fi rst, we investigate system ranking of top runs for three topic diffi culty levels $diff$, whose values are “hard,” “middle” or “easy” as defi ned in Subsec. 2.1. Here, the number of system search results is 26, as described in the beginning Section 2.1. The results are presented as Table 2, where $ave$ indicates the mean average precision for each run. Then, we obtained the respective average values of non-interpolated average precision for three topic diffi culty levels, and analyzed the rank correlation between them. The resulting Kendall’s $\tau$ and observed signifi cance level $\alpha$ are presented in Table 3.

Table 3 explains that the differences of system ranking is not signifi cant in spite of the differences of topic diffi culty. However, we can fi nd through Table 2 the cases when respective system ranks of top runs are changed in details according to topic diffi culty levels, where the improving rates of mean average precision reach 5%, the statistically signifi cant level (Kishida, 2001). This suggests that the topic diffi culty can affect the system ranks to some extent.

### 3.2. Preliminary Investigation on Topic Predictability

We investigate the correlation between the actual topic diffi culty based on submitted result set, the human-judged topic diffi culty based on function-based topic categorization and the other features of the topics. We made use of Kendall’s rank correlation coef fi cient $\tau$ to measure the correlations, because we consider that the comparative measures are more important than the absolute ones in this case of correlation analysis.

For computing the correlation, the actual topic diffi culty $diff$ has one of the values 1, 2 or 3 respectively corresponded to “easy,” “middle” or “hard,” and the human-judged diffi culty $func$ has one of the values 1, 2, · · · , 6 respectively corresponded to the A, B, · · · , F, shown in Table 1. The values of Kendall’s $\tau$ and their two-sided signifi cance level are indicated in Table 4, where $ave$, $stdev$, $med$, $skew$ and $kurt$ respectively indicate the average, standard derivation, median, skewness and kurtosis of the distribution of non-interpolated average precision using the submitted result set; $#rel$ and $#term$ respectively indicate the average number of relevant documents and topic terms. The following evidence can be found through Table 4.

(1) Both of the skewness ($skew$) and kurtosis ($kurt$) of the distribution of average precision have evident positive correlation with $diff$. Conversely, standard derivation ($stdev$) has evident negative correlation with $diff$. Those can be found in Figure 1. Thus, it appears that the more diffi cult the topics, namely the more they are shifted to the region of low average precision in the distribution of the average precision, the sharper the distribution becomes.

(2) Evident correlation cannot be seen between the two topic diffi culty indicators: $diff$, the actual diffi culty based on the submitted results, and $func$, the human-judged diffi culty using function-based topic categorization. In addition, we investigated the correlation between $diff$ and the other feature quantities within each
Table 4: Kendall’s rank correlation coefficients between the topic difficulty and feature quantities of the topics.

| diff | fune | \#rel | ave | std | med | skew | kurt | \#term | tf db | df db | tf df db |
|------|------|-------|-----|-----|-----|------|------|--------|-------|-------|---------|
|      |      |       |     |     |     |      |      |        |       |       |         |
| 0.094| 0.798| 0.680| 0.824| 0.659| 0.247| -0.068| 0.299| 0.333 | 0.312 | -0.291|
| 0.443| 0.424| 0.000| 0.000| 0.000| 0.000| 0.000| 0.000| 0.000 | 0.000 | 0.000 |
| 0.005| 0.092| 0.111| 0.110| 0.049| 0.028| 0.014| 0.026| 0.081 | 0.081 | -0.055|
| -0.119| -0.165| 0.119| 0.064| 0.063| 0.113| 0.123| 0.192| 0.065 | -0.110|
| 0.211| 0.080| 0.214| 0.504| 0.514| 0.285| 0.200| 0.040| 0.494 | 0.222|
| 0.000| 0.000| 0.000| 0.055| 0.541| 0.041| 0.000| 0.032| 0.038 |
| 0.790| 0.430| 0.182| 0.045| 0.147| 0.246| 0.134| 0.231|
| 0.000| 0.000| 0.005| 0.644| 0.119| 0.009| 0.156| 0.019 |
| -0.609| 0.206| 0.055| 0.229| 0.274| -0.231| 0.221|
| 0.010| 0.887| 0.066| 0.050| 0.036| 0.091|
| -0.086| 0.124| 0.112| -0.055| 0.094|
| 0.416| 0.182| 0.237| 0.581| 0.319|
| 0.171| 0.148| 0.148| -0.093|
| 0.084| 0.133| 0.133| 0.349|
| 0.805| 0.097| 0.000| 0.000| 0.000|
| 0.569| 0.417| 0.000|
| -0.237| 0.014|

Upper sections in each cell: Kendall’s \( \tau \); lower sections: observed two-sided significance level \( \alpha \); emphasized: correlation coefficients which are significant within 1\% two-sided significance level; underlined: correlation coefficients which are significant within 5\% two-sided significance level.

Figure 1: Histograms of medians of the non-interpolated average precision based on submitted results for three topic difficulty levels.

For the \( \text{fune} \) category, and investigated the correlation between \( \text{fune} \) and the others within each \( \text{diff} \) category. However, we found no evident correlation in the results.

(3) The average number of relevant documents (\#rel) and topic terms (\#term) do not have evident correlation with \( \text{diff} \).

(4) Kendall’s \( \tau \) between \( \text{tf db} \) and \( \text{df db} \) is larger than 0.80, and exhibits strong positive correlation in the statistical test. In addition, a \( \tau \) between \( \text{tf df db} \) and \( \text{df df db} \) exhibits strong negative correlation.\(^4\) Thus, it does not seem to make sense that \( \text{tf db} \) and \( \text{df db} \) (\( \text{tf df db} \) and \( \text{df df db} \)) are treated as independent feature quantities, as in Eqs.(3), (4). This can be found through the fact that \( \tau \) between \( \text{diff} \) and \( \text{tf db} \) (\( \text{df db} \)) nearly equal \( \tau \) between \( \text{diff} \)

\(^{4}\)This result is omitted in Table 4 because of lack of space.

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Figure 2: Box-and-whisker graph presenting the relation between $df_{db}$ and $df_{ff}$.

and $tfidf$ ($ltfidf$) in Table 4. Hereafter, we will suppose $df_{db}$ to be the typical feature quantity of those using frequency information in the document database. The $\tau$ between $df_{db}$ and $df_{ff}$ is more than 0.33, which is not a large value, but exhibits evident positive correlation through the statistical test. It also can be found in Figure 2. This suggests that the more frequently the topic terms appear in the document database, the less effectively the search can be achieved. However, it is not easy to predict the topic difficulty or its distribution using only the frequency information of the topic terms in the document database.

4. Conclusions

Respective system ranks of top runs may be significantly changed to topic difficulty although the differences of total ranking is not significant as the results of statistical tests. This suggests that the topic difficulty affects the system ranks to some extent.

Evident positive correlation can be found between the topic difficulty and the frequencies of the topic terms in the document database, but it does not have a large correlation coefficient. This suggests that the various IR methods that have been proposed so far tend to depend on the topic/query term frequencies in the document database.

Unfortunately, the evident correlation cannot be seen between two topic difficulty indicators: the actual difficulty based on submitted results and the human-judged difficulty using function-based topic categorization.

Further investigations on various features of the topics and their combinations are required to predict, for practical use, the topic difficulty or its distribution.

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