ICTCAS's ICTGrasper at TAC 2008: Summarizing Dynamic Information with Signature Terms Based Content Filtering

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Abstract

This paper presents our new, topic-oriented multi-document summarization system used in TAC 2008. To deal with the problem of summarizing changes of the dynamic information with time going, we propose a novel summarization method with signature terms based content filtering. We first present the definition of dynamic summarization according to temporal analysis and then propose the fundamental content filtering models for the identification of dynamic information, followed by a novel signature terms based re-ranking approach. The experimental results on the DUC 2007 update task indicate that significant improvements can be achieved through our proposed approaches as compared to the top performing systems in DUC tasks. We applied our proposed approach on the update summary task in TAC 2008 and achieved very competitive results.

1 Introduction

Every year, Document Understanding Conferences (DUC[1]) evaluates competing research groups' summarization systems on a set of summarization tasks. Piloted in DUC 2007, the update summarization task is to write a short ($\sim$ 100-word) multi-document summary of a set of newswire articles, under the assumption that the user has already read a given set of earlier articles. The topics and documents for the update pilot will be a subset of those for the main DUC task. The update task is a complex time-biased question-focused summarization task that requires summaries to piece together information from multiple documents to answer a question or a set of questions as posed in a DUC topic. The summaries will be evaluated for readability and content (based on ROUGE, BE, and Columbia University's Pyramid Method).

In the update task of DUC 2007, the task is to create short ($\sim$ 100 words) multi-document summaries. There are approximately 10 topics in the test data, with 25 documents per topic. NIST[2] Assessors developed a total of 10 DUC topics to be used as test data with 25 documents per topic. For each topic, the documents are ordered chronologically and then partitioned into 3 sets, $A - C$, where the time stamps on all the documents in each set are ordered such that $time(A) < time(B) < time(C)$. There will be approximately 10 documents in Set A, 8 in Set B, and 7 in Set C. The documents come from the AQUAINT collection of news articles, comprising newswire articles from the Associated Press and New York Times (1998-2000) and Xinhua News Agency (1996-2000).

Piloted in DUC 2007, the TAC 2008 Update Summarization task is to generate short ($\sim$100 words) fluent multi-document summaries of news articles under the assumption that the user has already read a set of earlier articles. The purpose of each update summary is to inform the reader of new information about a particular topic. The content of each submitted summary will be evaluated against multiple model summaries based on Columbia Univer-

[1]Document Understanding Conference, http://duc.nist.gov/

[2]National Institute of Standard and Technology, http://www.nist.gov/

sity's Pyramid method. The test dataset comprises approximately 48 topics. Each topic has a topic statement (title and narrative) and 20 relevant documents which have been divided into 2 sets: Document Set A and Document Set B. Each document set has 10 documents, where all the documents in Set A chronologically precede the documents in Set B. The documents come from the AQUAINT-2 collection of news articles. Each team may submit up to three runs (submissions) for the update summarization pilot task, ranked by priority. NIST will judge the first- and second-priority run from each team and (if resources allow) up to one additional run from each team. Runs must be fully automatic.

The topic statement could be in the form of a question or set of related questions and could include background information that the assessor thought would help clarify his/her information need. The assessor also indicated the "granularity" of the desired response for each DUC topic. That is, they indicated whether they wanted the answer to their question(s) to name specific events, people, places, etc., or whether they wanted a general, high-level answer. Only one value of granularity was given for each topic, since the goal was not to measure the effect of different granularity on system performance for a specified topic, but to provide additional information about the user's preferences to both human and automatic summarization.

As an effective and concise approach of helping users to catch the main points, document summarization has attracted much attention since the original work by Luhn (Luhn, 1958). A number of researchers have done good work in multi-document summarization (MDS). Unfortunately, much of their work has focused on the specified static document collection, without attempting to capture the changes over time. Furthermore, the difficulty of constructing an adequate model for the dynamically changing information itself is not fully recognized. The classic problem of summarization, simply put, is to take an information source, extract content from it, and present the most important content to the user in a condensed form and in a manner sensitive to the user's or application's needs (Mani, 2001), which has been studied in many variations and has been addressed through a rich diversity of summarization techniques (Erkan, 2004; Harabagiu, 2005; Shen, 2007; Zhang, 2008).

The goal of update summarization task is to provide concise, informative summaries of the periodical dynamic information devoted to a common topic thus saving the users from browsing the web content during long time. Besides its enormous size, the web content is also very dynamic-not only is information being continually added, it is also being continually removed and is often irrecoverably lost. From this perspective, the update summarization task is to generate the dynamical summarization indeed. Therefore, we can formulate the update summarization task as dynamic summarization. Dynamic summarization can be valuable for periodically monitoring the important changes for the new relevant information over a given time period. There are several situations when dynamic summarization can be of some value. Users may want to know the most important changes occurring in some domains (Jatowt, 2004; Jatowt, 2006). They can be interested in popular topics discussed in their area of interest or the changes in public opinions of web pages during a specified period. Additionally, dynamic summarization can also help predict the evolution trend of event in the web. Users can obtain the evolution trend from the sequence of summaries with time going. As a simple application of dynamic summarization, temporal summarization has attracted attention in Topic Detection and Tracking (TDT[3]). Several recent attempts have been made to capture dynamic information by topic detection and tracking (Allan, 1998; Swan, 2000; Zhang, 2002; Cao, 2007). As defined in (Allan, 2001), the temporal summarization is in fact a single-document summarization, which is to summarize a single web document over a given time interval. The temporal summarization focuses on the identification of changes between individual web document, however, the challenges of multi-document are seldom addressed.

Research studies on update task of DUC 2007[4] go further by using signature term and term frequency distribution to generate summaries (Conroy, 2007; Hickl, 2007). Unfortunately, these approaches are knowledge based, and the summaries mostly rely on the effectiveness of term's selection. What

[3]TDT, http://www.nist.gov/speech/tests/tdt/

[4]http://www-nlpir.nist.gov/projects/duc/duc2007/tasks.html

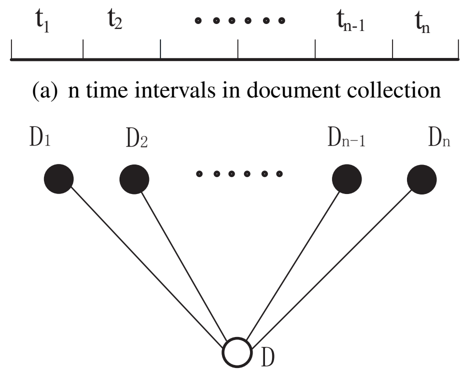
is ideal for us is to investigate a machine learning method based on the detection of dynamic information, which can filter the previous content so as to generate dynamic summary. In this paper, we introduce an extensive issue of multi-document summarization, dynamic summarization, to produce summary from the dynamically changing information in the document collection. Then we propose the fundamental content filtering models for the identification of dynamic information. In order to pursue for an effective rank algorithm to identify important sentence, a signature terms based re-ranking method is presented, follows by the investigation and evaluation of content filtering approaches. Experimental results on DUC 2007 dataset show that our signature terms based content filtering approach are competitive with state-of-the-art systems developed in these areas.

In Section 2 below we give an overview of the ICTGrasper system. In Section 3 we evaluate the contribution of our proposed signature terms based content filtering. Section 4 provides a short account of our effort to adapt ICTGrasper to the TAC 2008 update summarization task. Finally we conclude with a summary and discussion of our results in TAC 2008, and look ahead to future work.

2 The ICTGrasper System

In this section, we present an overview of the systems we used to generate multi-document summaries for the TAC 2008 Update Summarization Track. The architecture of the systems we developed is presented in Figure 1.

With ICTGrasper, topic-oriented multi-document summaries (such as those evaluated in the TAC 2008 Update Task) are generated in a three-step process. The first step is to segment document collection according to the temporal order with temporal analysis. Then, the second step is to identify the dynamic information with content filtering model. Finally, a signature terms based re-ranking criterion is employed to evaluate the importance of sentences, select the important sentences, and generate the dynamic summarization. In this work, ICTGrasper mainly comprises a content filtering model for dynamic information identification and a signature terms based re-ranking criterion for scoring sentences and summaries, which are described in the subsections below.



(a) n time intervals in document collection

(b) n sub-collections of D corresponding to the time intervals

Figure 2: Formalization of Dynamic Summarization

2.1 Definitions

For this study, we assume that the document collection can be broken into a sequence of document clusters according to time intervals, and a document cluster is considered to be a dynamic entity that changes and evolves over time (Jatowt, 2004). For a random variable t over time, and a random variable D, a document collection to be summarized, the document collection D can be divided into n intervals according to the time intervals. As Figure 1 shows, there are n time intervals in D (in Figure 1(a)), then D can be mapped to n sub-collections according to the time intervals (in Figure 1(b)).

In general, it is difficult to determine different content between n sub-collections. Hence, we make the following simplification that the whole document collection can be divided into two parts, current information and history information, where the sub-collection D_n is the current information, and the history information is the previous sub-collections from D_1 to D_{n-1} ($D_1 \sim D_{n-1}$). More precisely, we define the sentences of D_n as the current information, and the sentences of $D_1 \sim D_{n-1}$ as the history information.

With the above definition, the first challenge of dynamic summarization can be formulated as how to determine the dynamic/novelty content of current information according to the history information. In (Zhang, 2002), Zhang et al. proposed an adaptive in-

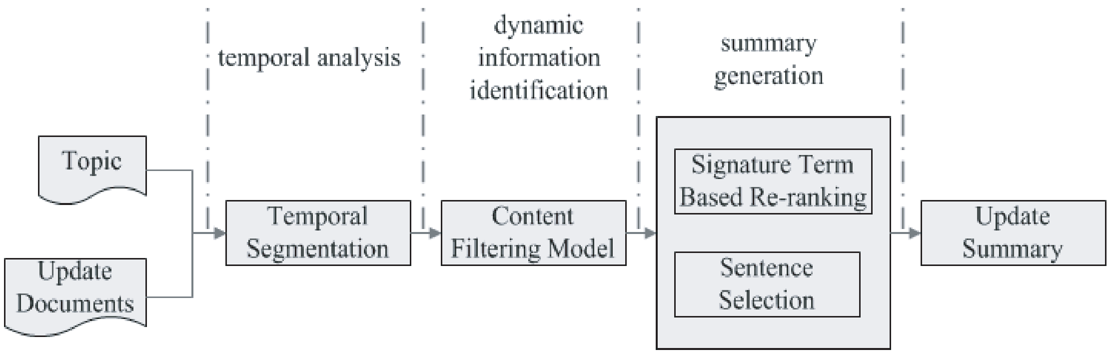


Figure 1: The framework of ICTGrasper system for dynamic summarization

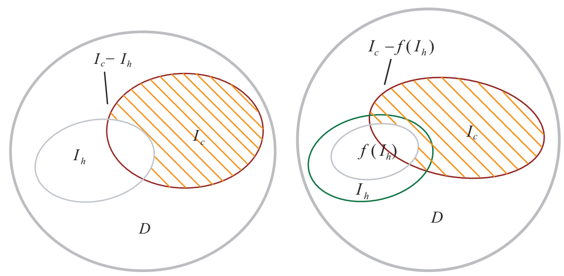
formation system to make decisions about the novelty and redundancy of relevant document. In the following section, we will address our approach that employs content filtering to make decisions about the novelty and redundancy of current information.

2.2 Content Filtering Models

As mentioned above, our objective is to construct summarization in dynamically changing document collection, and the first challenge is how to filter the redundant information from current information according to the history information. In order to filtering the redundant information, we use the degree of belongingness to measure the similarity of sentences between history information and current information. In this paper, degree is short for degree of belongingness. Since the aim of summarization is to extract content from a document collection, thus the summary of document collection is a proper subset of D_i with a special mapping, and this mapping relationship between document and summary can be represented as a variable f. Given the history information I_h, the current information I_c, degree, and mapping relationship f, there are three fundamental models for content filtering based on the objects to be filtered.

2.2.1 Document Filtering Model

The first content filtering model is document filtering model (DFM), where the object to be filtered is document collection of current information I_h itself. In the model we assume that the dynamic content is the sentences of I_c except the sentences redundant to I_h, and these redundant sentences can be filtered from I_c with a specified degree. For convenience, we use $I_c - I_h$ to denote the document filtering model. As Figure 3(a) illustrates, the shadow of I_c is the changing content to be summarized. In general, the summary of a document collection has high relevant to its content. Thus, in order to save the calculating cost of redundant content, the map of I_h in summary space, $f(I_h)$, is used to substitute I_h, then we can obtain an alternative model, $I_c - f(I_h)$, in Figure 3(b). In order to discriminate these two varieties, $I_c - I_h$ and $I_c - f(I_h)$ are denoted by *DFM1* and *DFM2* respectively.

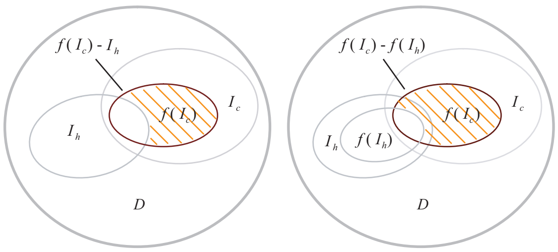


(a) $I_c - I_h$ (b) $I_c - f(I_h)$

Figure 3: Document Filtering Model

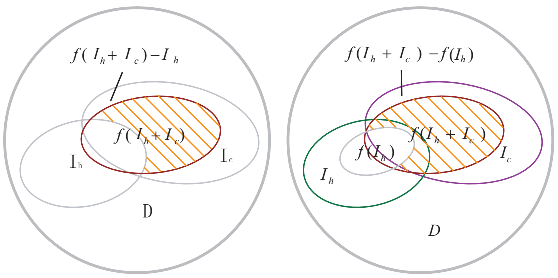
2.2.2 Summary Filtering Model

The second content filtering model is summary filtering model (SFM), where the object to be filtered is the summary of current information $f(I_c)$. In SFM, we assume that the dynamic summary can be generated by filtering the redundant sentences from $f(I_c)$ according to I_h. Intuitively, there are fewer sentences in summary, thus the calculating cost of redundant content of SFM is lower than that of DFM. Similarly, in order to further save filtering cost, I_h can be substituted with $f(I_h)$, then



(a) $f(I_c) - I_h$ (b) $f(I_c) - f(I_h)$

Figure 4: Summary Filtering Model



(a) $f(I_c + I_h) - I_h$ (b) $f(I_c + I_h) - f(I_h)$

Figure 5: Union Filtering Model

two varieties of SFM can be obtained as shown in Figure 4(a) and Figure 4(b). For convenience, *SFM1* and *SFM2* are used to denote $f(I_c) - I_h$ and $f(I_c) - f(I_h)$.

2.2.3 Union Filtering Model

With the assumption that the relation between history information and current information cannot be omitted, the dynamic summary can be generated from the union of I_h and I_c, in that the third content filtering model can be presented as union filtering model (UFM). Where the object of content filtering is the summary of the union of I_h and I_c. In like manner, two varieties of UFM, $f(I_c + I_h) - I_h$ and $f(I_c + I_h) - f(I_h)$ can be obtained (in Figure 5). Here, we use *UFM1* and *UFM2* to denote them respectively.

2.3 Signature Terms based Re-ranking

As mentioned in the above section, three fundamental models for content filtering were proposed. Once the content filtering model is certain, the remaining task is to purse for an effective rank algorithm to identify important sentences and generate dynamic summary. However, the importance of sentences is difficult to measure for the sentence's length is limited. In order to identify important sentences, the term expansion approach is needed. In practice, for highlighting some domain terms in specified document collection, we need to determine which terms are important, where these terms are called as signature terms. Loosely, signature terms are those terms which occur significantly more than expected "at large" (Dunning, 1993). Several computation methods for signature terms have been developed in previous work (Conroy, 2007; Hickl, 2007), unfortunately, they are obtained from supervised approaches and hard to implement. So we build our own computation method described as below.

2.3.1 Signature Term

In order to extract signature terms of document collection, we generate the n-grams of sentences in the document collection at first. The next step is to determine which n-grams are more important. In (Feng, 2004), Feng et al. proposed accessor variety criteria to extract meaningful string for Chinese document collection. They assumed that words have specific meanings because they are very widely used. With this assumption, we start our viewpoint that signature terms have wide usage and high occurrence for English, thus the signature terms can extract with two criteria, accessor variety (AV) and term frequency (TF). The algorithm of signature term extraction to document collection consists of the following main steps:

1. Identify n-grams ($n <= 5$) of the sentences set of document collection and add them into suffix tree.

2. Statistic the term frequency of each n-gram, and calculate the accessor varieties of bi-grams and tri-grams with accessor variety criterion.

3. Decrease n-grams with less AV and less TF to reserve significant terms.

4. Refine significant terms with similar form and same accessor variety according to diversity of TF.

The AV criterion is an important factor for determining the independence of the terms. In usual, the AV criterion is more important than TF criterion. In order to evaluate the significance of the terms quantitatively, we use the linear combination of AV and TF together as the hybrid score of term t.

$$Score(t) = \alpha * AV(t) + \beta * TF(t) \quad (1)$$

2.3.2 Signature Terms based Re-ranking

For summarization algorithm with specified sentences ranking criteria, the term expansion provides a re-ranking criterion to determine importance of sentences with given signature terms. Normally, signature terms can be used to optimize similarity measure by combining with the uni-grams in the vector space model (VSM). In this paper, we adapt a linear combination to optimize importance measure of sentence as follows:

$$Rank(s) = \alpha * cen(s) + \beta * sim(s, T) + \gamma * score(s|t) \quad (2)$$

where s is a sentence, and $Rank(s)$ is the importance rank of s. In the linear combination, $cen(s)$ is the centrality of s calculated with LexRank (Erkan, 2004), $sim(s, T)$ is the similarity between s and document collection's topic T, $score(s|t)$ is the score of s by taking into account signature terms, and α, β and γ are the weight factors. For a specified sentence s, and the signature terms of s, the $score(s|t)$ is computed as:

$$score(s|t) = \sum_{i=1}^{k} score(t_i) \quad (3)$$

where t_1,...,t_k are the signature terms in s, and $score(t_i)$ is the normalized score of t_i determined by AV or TF.

3 Experiments

In this section we discuss the performance of the system and analyze the contribution of the content filtering model and the signature terms based re-ranking criterion. We also analyze the performance of systems with comparison to the state-of-the-art top performing systems in previous DUC tasks.

Our proposed approach was trained on the DUC 2007 data of update task, using the content filtering models discussed in Section 2.2 and the signature terms based re-ranking criterion discussed in Section 2.3.

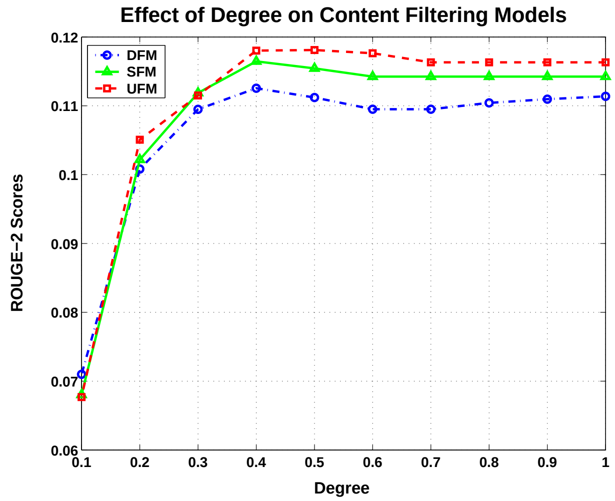


Figure 6: Effect of degree on content filtering models, where the ROUGE scores of degree from 0.1 to 1.0 with step 0.1 are plotted, and the highest values occurs when degree equals to 0.4.

The evaluation of our summarization approaches was driven by two questions: (1) Do the content filtering models produce summaries of acceptable quality, and which model is most suitable for dynamic summarization? (2) Does signature terms based re-ranking provide significant advantages?

3.1 Performance of Content Filtering Models

To address the first question, we compare the ROUGE (Lin, 2004) scores generated from these three content filtering models. In Table 1, we present the results of three types of $NaiveTCFM$ (DFM, SFM and UFM) with two degrees (1.0 and 0.4) respectively. As Table 1 shows, the difference of *DFM2* is not significant with different degrees ($< 0.5\%$), while the differences of other models arrange from 1.1% to 2.3%. The results indicate that *UFM1* can be the optimal content filtering model for dynamic summarization. We also investigated how sensitive *UFM1* is with respect to degree from 0.1 to 1.0 with step 0.1. Figure 6 shows the ROUGE-2 scores and ROUGE-SU4 scores of content filtering models (*DFM1*, *SFM1*, and *UFM1*) for a range of degrees. This figure shows that R-2 and R-SU4 synchronously increase and decrease with variety of degrees. The highest values of both occur when degree is 0.4.

Table 2 gives further details on the performance

Table 1: The results of three models for dynamic summarization, where the degree denotes the degree of membership in set, R-2 and R-SU4 are the scores of ROUGE-2 and ROUGE-SU4 on dataset of DUC 2007 update task.

	DFM1		DFM2		SFM1		SFM2		UFM1		UFM2	
Degree	R-2	R-SU4	R-2	R-SU4	R-2	R-SU4	R-2	R-SU4	R-2	R-SU4	R-2	R-SU4
1.0	0.1114	0.1450	0.1142	0.1482	0.1142	0.1482	0.1142	0.1482	**0.1163**	**0.1492**	0.10268	0.13847
0.4	0.1126	0.1467	0.1146	0.1478	0.1165	0.1495	0.1142	0.1482	**0.1180**	**0.1506**	0.1050	0.1398

comparison with stat-of-the-art systems and generic baseline of DUC 2007 update task, where the ROUGE scores are the values obtained when degree is 0.4. LCC, IIIT and NUS are the top three systems this year, and the scores of these three systems and generic baseline are provided by DUC. With comparison to these systems, our *UFM1* can exceed LCC on ROUGE-SU4 about and 5.2% on ROUGE-2. Moreover, with comparison to the 2nd rank system IIIT, our *UFM1* can gain improvement about 19.8% and 11.4% on ROUGE scores respectively. The results confirm our hypothesis about the benefits of content filtering models for dynamic summarization.

Table 2: Performance comparison with state-of-the-art systems of DUC 2007 update task, where $UFM1$ represents the performance of our proposed union filtering model, LCC, $IIIT$, and NUS are the top performing systems.

System	ROUGE-2	ROUGE-SU4
UFM1(Degree=0.4)	**0.1180**	**0.1506**
LCC (Rank 1)	0.1119	0.1431
IIIT (Rank 2)	0.0985	0.1352
NUS (Rank 3)	0.0962	0.1325
Generic Baseline	0.0850	0.1225

3.2 Performance of Signature Terms

To address the second question, we compare the results of the system signature term based *UFM1* (*UFM1-S*) and the system without consideration signature term *UFM1* (*UFM1-N*) in Table 3. Not surprisingly, performance improvement for both ROUGE-2 and ROUGE-SU4 is very obvious. With comparison to LCC, *UFM1-S* can gain improvement about 8.9% and 10.5% on both two scores of ROUGE respectively. Interestingly, the re-ranking score of *UFM1-S* is not depend on the AV score but the TF score of signature terms, that can be thought of the TF score as being more precious, in that the signature terms have been filtering by AV score - that is, TF score can be seen a fusion score by combination with AV and TF.

Table 3: The performances of signature terms, where UFM1-N is the system with UFM1 but without consideration signature terms, and UFM1-S is the system with signature term based UFM1.

System	ROUGE-2	ROUGE-SU4
UFM1-S	**0.1219**	**0.1581**
UFM1-N	**0.1180**	**0.1506**
LCC	0.1119	0.1431

4 Results in TAC 2008 Update Summarization Task

The update summarization task in TAC 2008 required participants to generate 100-word summaries of 48 clusters of 25 newswire documents each in response to short questions about their content. In order to summarizing the dynamic information, we employed our proposed signature terms based content filtering to construct the dynamic summaries. With the content filtering models proposed in Section 2.2, three varieties of summaries, Run 14, Run 65, and Run 44, were then constructed with corresponding to $UFM1$, $SFM1$ and $SFM2$ respectively. The three submitted runs of ICTCAS's ICT-Grasper (Run 14, Run 44 and Run 65) obtained very competitive results across all evaluation metrics for the TAC 2008 Update Summarization Track. ICT-

Grasper (as Run 14 and Run 65) placed 3rd and 5th out of 71 runs participating in the ROUGE-2 evaluation, and placed 5th and 9th out of 71 runs participating in the ROUGE-SU4 evaluation. Moreover, these two runs of ICTGrasper obtained the top 2 places in the BE evaluation. In the manual evaluation, the runs of ICTGrasper are also very competitive, and the two runs of ICTGrasper placed 2nd and 3rd in the average modified (pyramid) score. On these metrics, the upper bound of the confidence interval overlaps with the lower bound of the confidence intervals of 4 human summarizers (A, B, E, and C).

Table 4: The evaluation results of TAC 2008 top performing systems, where $R-2$ and $R-SU4$ stand for the ROUGE-2 and ROUGE-SU4 scores in ROUGE evaluation. For convenience, only four runs with stable performance are illustrated in this table, and Run 14 and Run 65 are two runs of ICTGrasper.

	ROUGE				BE	
Run	R2	Rank	R-SU4	Rank	BE	Rank
14	0.09776	3	0.13295	5	0.06480	1
65	0.09559	5	0.13151	9	0.06293	2
43	0.10395	1	0.13646	1	0.06267	3
60	0.09449	6	0.13583	3	0.06203	4

For there is no history information for the first sub-collection, the summarizing process of Document Set A is no difference from static summarization. Therefore, the performance of dynamic summarization should focus on the evaluation on the second sub-collection, Document Set B. In order to prove the effectiveness of our proposed approach, we first investigate the performance of ICTGrasper on the second document set. The best run of ICTGrasper (Run 14) placed 1st on the modified Pyramid score-B scores, 2nd on the average numSCUs-B scores in manual evaluation. And in the automatic evaluation, Run 14 obtained all the first places on ROUGE and BE metrics. As Table 5 shows, the performance of our propose approach is very significant on Document Set B. Furthermore, we conducted another experiment to compare the performance of TAC 2008 top performing systems on two sub-collections respectively. As Figure 7 shows, although the best run of ICTGrasper (Run 14) can not perform the best on Document Set A, Grasper can obtain significant improvement on the second document set. This figure illustrates our proposed approach is really effective for dynamic summarization with time going. Moreover, we believe that when a more significant performance obtained in static summarization, our system will give a more significant performance.

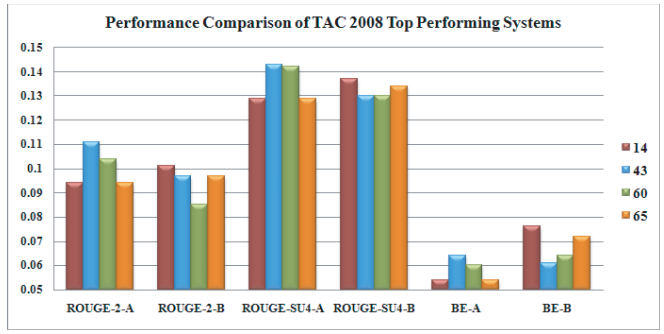


Figure 7: Performance comparison of TAC 2008 top performing systems on document set A and B, where Run 14 is the system with our proposed approach.

Table 5: The performances of Grasper's best run (Run 14) on the Document Set B.

Metric	Score	Rank
mod Pyramid score - B	0.344	1
numScus - B	4.063	2
ROUGE-2 Recall - B	0.101	1
ROUGE-SU4 Recall - B	0.137	1
BE Recall - B	0.076	1

5 Conclusion and Future Work

In this paper, we introduced a novel summarization approach for dynamic information with content filtering models, and three fundamental models for content filtering as the objects to be filtered were presented. Furthermore, in order to further improve the precision and effectiveness of dynamic summarization, a novel approach of signature term extraction was proposed to rerank the importance of filtered content. With the signature term based reranking, our union filtering model yields significant improvement over the previously proposed methods in DUC 2007 update task. As part of TAC 2008, we participate in the update summary task. The results are competitive and show that our proposed approach works very well in update task. We believe that when a more significant performance obtained in static summarization, our system will give a more significant performance.

6 Acknowledgements

This work is supported by The 973 National Basic Research Program of China (2004CB318109) and The 863 National High-Tech Research and Development Plan of China (2006AA01Z452 & 2007AA01Z438 & 2007AA01Z441).

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