Extractive Summarization Based on Event Term Temporal Relation Graph and Critical Chain

Maofu Liu[1], Wenjie Li[2], and Huijun Hu[1]

[1] College of Computer Science and Technology,
Wuhan University of Science and Technology, Wuhan, P.R.China
{liumaofu,huhuijun}@wust.edu.cn
[2] Department of Computing, The Hong Kong Polytechnic University, Kowloon, Hong Kong
cswjli@comp.polyu.edu.hk

Abstract. In this paper, we investigate whether temporal relations among event terms can help improve event-based extractive summarization and text cohesion of machine-generated summaries. Using the verb semantic relation, namely *happens-before* provided by VerbOcean, we construct an event term temporal relation graph for source documents. We assume that the maximal weakly connected component on this graph represents the main topic of source documents. The event terms in the temporal critical chain identified from the maximal weakly connected component are then used to calculate the significance of the sentences in source documents. The most significant sentences are included in final summaries. Experiments conducted on the DUC 2001 corpus show that extractive summarization based on event term temporal relation graph and critical chain is able to organize final summaries in a more coherent way and accordingly achieves encouraging improvement over the well-known tf*idf-based and PageRank-based approaches.

1 Introduction

Extractive summarization selects the most representative sentences from source documents. Under the extractive summarization framework, event has been regarded as an effective concept representation in recently emerged event-based summarization, which extracts salient sentences from single document or multiple documents and re-organizes them in a machine-generated summary according to how important the events that sentences describe are. With regard to the definition of events, in conjunction with the common agreement that event contains a series of happenings, we formulate events as "[Who] did [What] to [Whom] [When] and [Where]" at sentence level in the context of event-based summarization. In this paper, we focus on "did [What]" and approximately define verbs and action nouns in source documents as *event terms* that characterize or partially characterize event occurrences.

Notice that in addition to the quality and the quantity of the informative contents conveyed in the extracted sentences, the relations among the extracted sentences, such as temporal relations in news articles, and structure of the final summary text should be a matter of concern. The sentence relations in source and summary text, if appropriately defined and identified, are a good means to reflect the text cohesion, i.e. the way of getting the source and extracted text to "hang together" as a whole and the

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indicator of text unity. In the literature, text cohesion has been modeled by lexical cohesion in terms of the semantic relations existing between not only pairs of words but also over a succession of a number of nearby related words spanning a topical unit of the text. These sequences of related words are called lexical chains and tend to delineate portions of the text that have a strong unity of meaning.

Lexical chains have been investigated for extractive summarization in the past. They are regarded as a direct result of units of text being "about the same thing" and having a correspondence to the structure of the text. Normally, nouns or noun compounds are used to denote the things and compute lexical chains (i.e. lexical chains are normally noun chains). In this paper, we assume that the source text describes a series of events via the set of sentences and take both informative content and structure of the source text into consideration. We look for the event term *temporal critical chain* in the event term temporal relation graph and use it to represent the source text and to generate the final summary. We concentrate on verb chains, other than noun chains, aiming at improving event-based summarization and lexical cohesion of the generated summaries. Here, event terms and event term chain characterize informative content and text cohesion, respectively.

To compute the event term temporal critical chain, event terms are connected to construct an *event term temporal relation graph* based on the *happens-before* relations provided in VerbOcean. This type of relations indicates that the two verbs refer to two temporally disjoint intervals or instances [16]. The DFS-based (Depth-First Search) algorithm is applied in searching the temporal critical chain. Then the event terms in the temporal critical chain are used to evaluate sentences. The sentences with the highest significance scores are extracted to form the final summary.

The remainder of this paper is organized as follows. Section 2 reviews related work. Section 3 introduces the proposed event-based summarization approach based on event term temporal relation graph and critical chain. Section 4 then presents experiments and discussions. Finally, Section 5 concludes the paper and suggests the future work.

2 Related Work

Daniel et al. [1] pilot the study of event-based summarization. They recognize a news topic as a series of sub-events according to human understanding of the topic and investigate whether identifying sub-events in a news topic can help capture essential information in order to produce better summaries. Filatova and Hatzivassiloglou [2] then define the concept of atomic events as a feature that can be automatically extracted. Atomic events are defined as the relations between the important named entities. The proposed approach is claimed to outperform conventional tf*idf approach and experimental results indicate that event is indeed an effective feature for producing better summaries. Allan et al. [3] present a list of events within the topic in the order those events are reported and produce a revised up-to-date summary at regular time intervals. Afantenos et al. [5] discuss the techniques to summarize events happened in predictable time synchronously. Relations between events are defined on the axes of time and information source. Lim et al. [4] group source documents on time slots by the time information given in newspaper articles or publication dates. They build the local or global term cluster of each time slot and use it to identify a topical sentence as the representative for the time slot. Jatowt and Ishizuka [6] introduce the approaches to monitor the trends of dynamic web documents, which are different versions of documents on the time line. Based on distributions, terms are scored in order to identify whether they are popular and active. They employ a simple regression analysis of word frequency and time. Wu et al. [7] investigate whether time features help improve event-based summarization. After anchoring events on the time line, two different statistical measures, *tf*idf* and x^2, are employed to identify importance of events on each date.

The concept of lexical chain is originally proposed to represent the discourse structure of a document by Morris and Hirst [8]. They define lexical chain as a cluster of semantically related terms and construct lexical chains manually from Roget's Thesaurus according to the distance between the occurrences of related nouns and use lexical chain as an indicator of lexical cohesion of the text structure and the semantic context for interpreting words, concepts and sentences. Barzilay and Elhadad [9] first introduce lexical chain in single document summarization. They produce a summary of an original text relying on a model of the topic progression in the text derived from lexical chains. The lexical chains are computed using relatedness of nouns determined in terms of the distance between their occurrences and the shape of the path connecting them in the WordNet thesaurus. Following the same line of thought, Silber and McCoy [10, 11] employ lexical chains to extract important concepts from the source document and make lexical chains a computationally feasible candidate as an intermediate representation. Doran et al. [12] highlight the effect of lexical chain scoring metrics and sentence extraction techniques in summary generation. Zhou et al. [13] adapt lexical chains derived from WordNet based on noun compounds, noun entries and name entities to multi-document and query based summarization. Reeve et al. [14, 15] apply lexical chain based summarization approach to biomedical text. They build concept chains to link semantically-related concepts. The concepts are not derived from WordNet but domain-specific semantic resources, such as UMLS Metathesaurus and semantic network. The resulting concept chains are used to identify candidate sentences useful for summarization.

At present, the applications of temporal information in summarization are mostly based on time information in the source document or publication date. Meanwhile, the lexical chains mentioned above are all based on nouns, derived from WordNet or domain specific knowledge base. In this paper, we derive temporal information from the temporal relations among event terms and regard the event term temporal chains as the immediate representation of the source documents.

3 Summarization Based on Event Term Temporal Relation Graph and Critical Chain

In this section, we first illustrate how the event term temporal relation graph is constructed based on *happens-before* relation in VerbOcean. Then we explain how the event term temporal critical chain is determined from the temporal graph. Finally, sentence selection based on the significance of the event terms in the temporal critical chain is introduced.

3.1 Event Term Temporal Relation Graph Construction

In this paper, we introduce VerbOcean, a broad-coverage repository of semantic verb relations, into event-based extractive summarization. Different from other thesaurus like WordNet, VerbOcean provides five types of semantic relations among verbs at finer level. This just fits in with our idea to introduce event term semantic relations into summarization. In this paper, only *happens-before* temporal relation is explored. When two events happen, one may happen before the other. This is defined as *happens-before* temporal relation in VerbOcean. Examples of *happens-before* relations are illustrated below.

"wit" *happens-before* "record"
"move" *happens-before* "run"

The happens-before temporal relations on a set of event terms can be naturally represented by a graph, called event term temporal relation graph. We formally define the event term temporal relation graph connected by temporal relation as G=(V, E), where V is a set of event term vertices and E is a set of edges temporally connecting event terms. Fig.1 below shows a sample of event term temporal relation graph built from a DUC 2001 document set.

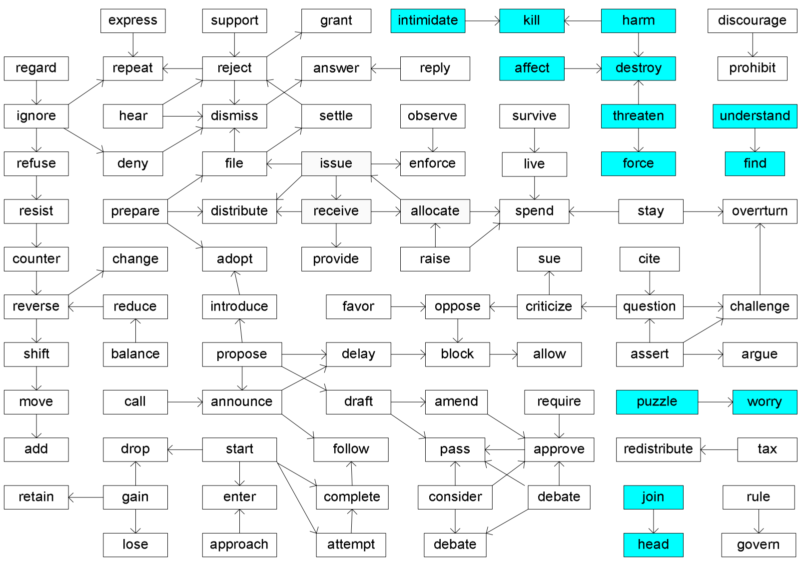

Fig. 1. Event term temporal graph based on happens-before relation

As we know, the graph is directed if the relation has the property of the anti-symmetric and undirected otherwise. Certainly, the event term temporal relation graph is a directed graph because *happens-before* relation in VerbOcean clearly exhibits the conspicuous anti-symmetric property. For example, one may "question" something and then decide to "criticize" it for some reason. The event represented by the term "question" *happens-before* the one represented by the term "criticize". So, a directed edge from "question" to "criticize" appears in Fig. 1.

The *happens-before* relation is also anti-reflexive because each event term cannot *happens-before* itself. This means that there is no self-loop at each term vertex. There are no parallel edges between any two adjacent term vertices either. Therefore, we can say that the event term temporal relation graph is a simple directed graph. In fact, *happens-before* relation is a transitive one, though there may not be an explicit edge from event term et_a to et_c when the edges both from et_a to et_b and from et_b to et_c exist. For example, there is no edge from "regard" to "repeat", but the edges exist from "regard" to "ignore" and from "ignore" to "repeat" in Fig. 1.

3.2 Event Term Temporal Critical Chain Identification

The event term temporal graph based on *happens-before* relation is not a fully connected graph. For example, there are eight sub-graphs or components in the graph illustrated in Fig. 1. Among them, a maximal weakly connected component, which contains the maximal number of the event terms, can be found. We assume that the event terms in the maximal weakly connected component reflect the main topic of original documents since such a component normally involves much more connected (i.e. relevant) event terms than any other components on the graph. Referring back to Fig. 1, the maximal weakly connected component contains 118 event terms, while the second largest weakly connected component contains only 8. Note that, for illustration purpose, only a partial maximal weakly connected component is shown in Fig. 1.

Some maximal weakly connected sub-graphs are cyclic. The graph in Fig. 2(a), a part of maximal weakly connected sub-graph in Fig. 1, is cyclic. We can see that there are cyclic relations among the three event terms "issue", "receive" and "allocate". In such a situation, the edge whose terminal term vertex has the maximal in-degree is removed in order to avoid the infinite loop in the identification of the event term temporal critical chain. Anyway, the terminal term can still be reached from other term vertices. The connection remains. For example, we remove the edge from "receive" to "allocate" in Fig. 2(a) and obtain a directed acyclic graph in Fig. 2(b).

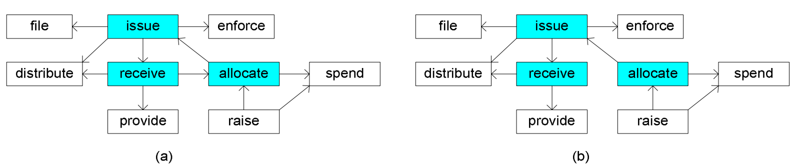

Fig. 2. The cyclic and acyclic graph part

From the directed acyclic graph, we extract all the source vertices and the sink vertices. The source vertex is defined as a vertex with successors but no predecessors, i.e. the edges being incident out of it but no edge being incident on it. On the contrary, the sink vertex is defined as a vertex with predecessors but no successors, i.e. the edges being incident on it but no edge being incident out of it. All source vertices and sink vertices in the directed acyclic graph of the maximal weakly connected component in Fig. 1 is shown in Fig. 3.

source vertices:
{regard, call, prepare, balance, hear, express, support, start, approach, require, debate, assert, cite, stay, survive, reply, observe, raise, gain, propose}

sink vertices:
{add, allow, answer, challenge, retain, lose, enter, change, repeat, adopt, provide, sue, spend, grant, overturn, argue, enforce, distribute }

Fig. 3. The source vertices and sink vertices of the directed acyclic graph

All directed paths from each source vertex to each sink vertex in the directed acyclic graph of the maximal weakly connected component are computed by the DFS-based algorithm. The longest path is defined as the event term temporal critical chain. The directed paths in Fig. 4 (a)-(d) are four event term chains found in Fig. 1 and the one in Fig. 4(a) is identified as the event term temporal critical chain.

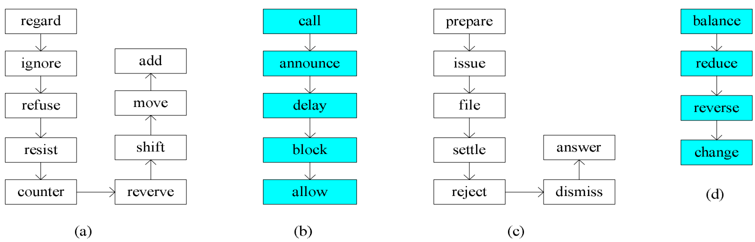

Fig. 4. The event term temporal critical chain for Fig. 1

Afterwards, we evaluate the sentences that contain the event terms in the chain and determine which ones should be extracted into the final summary based upon the event term temporal critical chain computation.

3.3 Sentence Selection

To apply the event term temporal critical chain in summarization, we need to identify the most significant sentences that best describe the event terms in the chain. Considering terms are the basic constitution of sentences, term significance is computed first. Since this paper studies event-based summarization, we only consider event terms and compute the significances of the event terms in the maximal weakly connected component of an event term temporal relation graph.

Two parameters are used in the calculation of event term significance. One is the occurrence of an event term in source documents. The other is the degree of an event term in an event term temporal relation graph. The degree of a term vertex in the directed graph is the sum of the in-degrees and out-degrees of that term.

For each event term in the temporal critical chain, it is likely to locate more than one sentence containing this term in source documents. We extract only one sentence for each event term to represent the event in order to avoid repeating the same or quite similar information in the summary. For sentence selection, the sentence significance is computed according to the event terms contained in it.

Based on event term occurrences, the significance of a sentence is calculated as

$$SC_i = \frac{TFS_i}{TFS_m} \tag{1}$$

where TFS_i and TFS_m are the sum of the term occurrences of the i^{th} sentence and the maximum of all the sentences that contain event terms in the temporal critical chain, respectively.

Alternatively, we can use degrees of event terms to calculate the significance of a sentence.

$$SC_i = \frac{DS_i}{DS_m} \tag{2}$$

where DS_i and DS_m are the sum of the term degrees of the i^{th} sentence and maximum of all the sentences which contain event terms in the temporal critical chain, respectively.

It should be emphasized here that the event terms under concern in Equations (1) and (2) must be the ones in the maximal weakly connected component of the event term temporal relation graph.

4 Experiment and Discussion

We evaluate the proposed summarization approach based on the event term temporal relation graph and critical chain on the DUC 2001 corpus. The corpus contains 30 English document sets. Among them, 10 sets are observed to contain descriptions of event sequences. They are the main concern of this paper. All final summaries are generated in 200 words length.

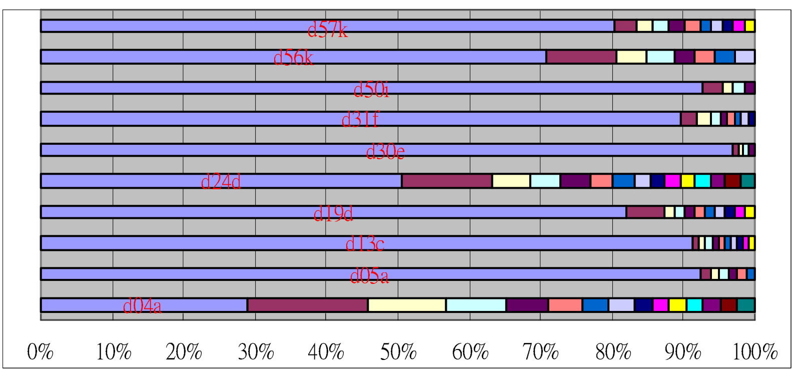

Fig. 5. The vertex number of the weakly connected components

The number of term vertices in the weakly connected component for each of 10 sets is illustrated in Fig. 5. Each bar denotes all weakly connected components of an event term temporal relation graph and the length of each series represents the vertex number in the weakly connected component. In Fig. 5, we can see that the numbers of the term vertices in maximal weakly connected components are actually much larger than the numbers of the term vertices in other components on the event term temporal relation graphs. For example, the maximal weakly connected component of the document set "d30e" almost includes all the vertices on its event term temporal relation graph. The other three document sets, i.e. "d05a", "d13c" and "d50i", occupy above 90% vertices. The minimum of the vertex number of the maximal weakly connected component in the "d04a" document set also includes almost 30% vertices. The assumption that the main topic of a document set can be represented by the maximal weakly connected component is not unreasonable. The maximal weakly connected component roughly describes all the events about main topic of the source documents in detail.

For 190 years, said Sen. Daniel Patrick Moynihan (D-N.Y.), the federal government has counted all inhabitants without regard to citizenship in accordance with the Constitution's provisions.
Groups which have filed suit to ignore the aliens contend large concentrations of them could result in some states gaining seats in the House of Representatives at the expense of other states.
Asking people about their status likely would result in people lying or refusing to participate in the count, officials say, resulting in a potential undercount of residents in many areas.
But he added that he is "optimistic, cautiously optimistic," that House conferees would resist the Senate-approved ban and not force Bush to veto the legislation.
Sen. Pete Wilson (R-Calif.) countered that excluding illegal residents from the decennial census is unfair to the states that have suffered from a huge influx of immigration beyond the legal limits.
The Senate's action was sharply criticized by Undersecretary of Commerce Michael Darby, but he voiced hope that it would be reversed by a Senate-House conference.
There could be enough of them to shift seats away from at least five states to Sun Belt states with large numbers of illegal residents.
The amendment was adopted after the Senate voted 58 to 41 against a move to reject it, and 56 to 43 against scuttling it as unconstitutional.

Fig. 6. The final summary for Fig. 4(a) based on vertex degree

The final summary shown in Fig. 6 is generated from the event term temporal relation graph in Fig. 1 and the event term temporal critical chain in Fig. 4(a) according to the calculation of sentence significance based on the vertex degree. The corresponding source document set is about the topic "whether to exclude illegal aliens from the decennial census and the final vote result of the Congress". We can see that the final summary indeed talks about the resident census history, the exclusion announcement, the reasons of the agreement and rejection, and the vote result. More important, the event term temporal critical chain contributes to the cohesion of the final summary. The summary has apparently shows temporal characteristic in sentence sequences, from resident census history, exclusion announcement and reasons for agreement and rejection to Senate vote result at the end.

To evaluate the quality of generated summaries, an automatic evaluation tool, called ROUGE [17] is used. The tool presents three ROUGE values including unigram-based ROUGE-1, bigram-based ROUGE-2 and ROUGE-W which is based on longest common subsequence weighted by the length.

In Fig. 7, the tf*idf approach is based on term frequency and inverse document frequency (a well-known statistical feature used in automatic summarization). We calculate tf*idf weights for all the words excluding stop-words and evaluate sentence significance using the SUM of tf*idf weights of all words occurring in the sentence. For the term occurrence approach, Equation (1) is adopted to calculate the significance of the sentence containing the event terms in the temporal critical chain using term occurrences. The comparative experiment results for the selected ten document sets are illustrated below.

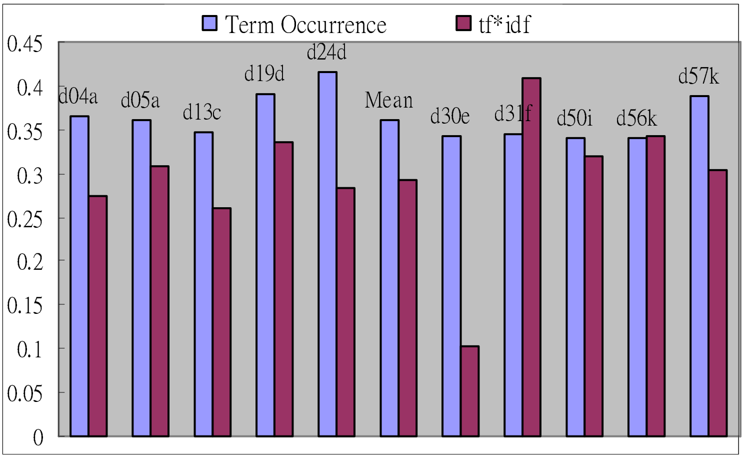

Fig. 7. ROUGE-1 scores on Term Occurrence and tf*idf

Except for the document sets "d31f" and "d56k", the experiment results based on event term occurrence in the critical temporal chains are all better than those based on tf*idf. In particular, event term occurrence achieves about 47.2% improvement on ROUGE-1 comparing to tf*idf for the document set "d24d".

Table 1. ROUGE scores on Term Occurrence and tf*idf

	tf*idf	Term Occurrence	Improvement
ROUGE-1	0.29222	0.36118	23.6%
ROUGE-2	0.04494	0.06254	39.2%
ROUGE-W	0.10099	0.12877	27.5%

Table 1 above shows the average ROUGE scores of event term occurrence and tf*idf approaches on the ten selected document sets. The ROUGE-2 score of the event term occurrence approach is comparatively about 39.2% better than the tf*idf approach. Our approach also shows more advantageous than the tf*idf approach on both ROUGE-1 and ROUGE-W. We highlight the ROUGE-2 scores here because we take semantic relevance between the events into account but tf*idf does not.

Google's PageRank [18] is one of the most popular ranking algorithms. It is a kind of graph-based ranking algorithm deciding on the importance of a node within a graph by taking into account the global information recursively computed from the entire graph. After constructing the event term temporal relation graph, we can also use the PageRank algorithm to calculate the significance of the terms in the graph. Because the calculations of sentence significance using PageRank and vertex degree are both based on the links among the vertices in the graph, we compare the ROUGE scores of the event term temporal critical chain based summarization using the vertex degree in sentences selection to those of PageRank-based approach. The experiment results of them are illustrated in the following Fig. 8.

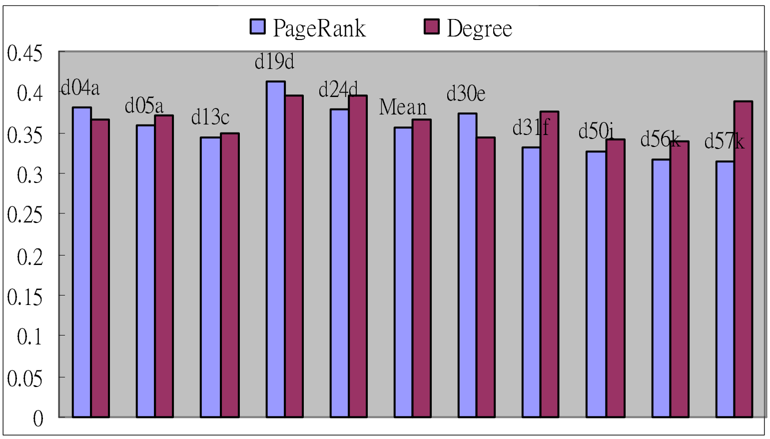

Fig. 8. ROUGE-1 scores on PageRank and Degree

Except for the document sets "d31f" and "d57k", the experiment results of event term degree approach are quite close to those based on the PageRank algorithm. For "d57k", the ROUGE-1 score of the event term degree approach is 0.38744 while the same of the PageRank algorithm is only 0.31385. It is about 23.4% of improvement. Table 2 below compares the average ROUGE scores of the two approaches. The ROUGE-1 score of the event term degree approach is about 2.5% above the ROUGE-1 score of the PageRank algorithm while the ROUGE-2 scores of them are quite similar. This is mainly because both the degree and the PageRank approaches take the semantic relevance between event terms into consideration in the calculation of significances of event terms and sentences.

Table 2. ROUGE scores on PageRank and Degree

	PageRank	Degree	Improvement
ROUGE-1	0.35645	0.36546	2.5%
ROUGE-2	0.06403	0.06490	1.6%
ROUGE-W	0.12504	0.13021	4.1%

Table 3. ROUGE scores on Term Occurrence and Degree

	Term Occurrence		Degree	
	Ten Sets	Twenty Sets	Ten Sets	Twenty Sets
ROUGE-1	0.36118	0.30453	0.36546	0.30099
ROUGE-2	0.06254	0.04390	0.06490	0.04449
ROUGE-W	0.12877	0.10861	0.13021	0.10803

Table 3 finally compares the average ROUGE scores of the ten document sets selected for the experiments above and the other twenty document sets in the DUC 2001 corpus with term occurrence and event term degree respectively. The ROUGE-1 average scores of the twenty document sets are much worse than the average scores of the ten document sets, i.e. about 15.7% lower using term occurrence and 17.6% lower using event term degree. The similar conclusions can be drawn on ROUGE-2 and ROUGE-W. This suggests that the proposed event-based approaches indeed can handle those documents describing events or event sequences much better. But they may not suit event irrelevant topics.

While the previously presented results are evaluated on 200 word summaries, now we move to check the results in the other three different sizes, i.e. 50, 100 and 400 words and the experiments results based on Degree and PageRank are in Table 4.

Table 4. ROUGE scores on PageRank and Degree with different summary lengths

Degree	50	100	400	PageRank	50	100	400
ROUGE-1	0.22956	0.28987	0.42475	ROUGE-1	0.20477	0.27250	0.42907
ROUGE-2	0.02550	0.04471	0.10186	ROUGE-2	0.02063	0.03933	0.10393
ROUGE-W	0.09655	0.11557	0.13763	ROUGE-W	0.08759	0.10849	0.13839

The experiment results in Table 4 show that our approach using event term degree makes much better results in 50 and 100 words summaries. We can also find that our approach prefers shorter summaries comparing with the PageRank approach in 400 words summaries. Of course, we need to test on more data in the future.

5 Conclusions and Future Work

In this paper, we investigate whether temporal relation between events helps improve performance of event-based summarization. By constructing the event term temporal graph based on the semantic relations derived from the knowledge base VerbOcean and computing weakly connected components, we find that the maximal weakly connected component can often denote the main topic of the source document.

Searching in the maximal weakly connected component with DFS-based algorithm, we can discover an event term temporal critical chain. The event terms in this chain are supposed to be critical for generating the final summary. In experiments, the significance of these terms is measured by either term occurrence in source documents or the degree in the constructed graph. The ROUGE results are promising.

Term occurrence significantly outperforms tf*idf and term degree is also comparative to well-known PageRank.

In the future, we will introduce the other types of VerbOcean verb semantic relations into event-based summarization. Besides the temporal critical chain in the event term relation graph, we will investigate the other possible event term temporal chains in the semantic computation. We also plan to combine the surface statistical features and the semantic features during the selection of representative sentences in order to generate better summaries.

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