Timestamped Graphs: Evolutionary Models of Text for Multi-document Summarization

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Abstract

Current graph-based approaches to automatic text summarization, such as LexRank and TextRank, assume a static graph which does not model how the input texts emerge. A suitable evolutionary text graph model may impart a better understanding of the texts and improve the summarization process. We propose a timestamped graph (TSG) model that is motivated by human writing and reading processes, and show how text units in this model emerge over time. In our model, the graphs used by LexRank and TextRank are specific instances of our timestamped graph with particular parameter settings. We apply timestamped graphs on the standard DUC multi-document text summarization task and achieve comparable results to the state of the art.

1 Introduction

Graph-based ranking algorithms such as Kleinberg's HITS (Kleinberg, 1999) or Google's PageRank (Brin and Page, 1998) have been successfully applied in citation network analysis and ranking of webpages. These algorithms essentially decide the weights of graph nodes based on global topological information. Recently, a number of graph-based approaches have been suggested for NLP applications. Erkan and Radev (2004) introduced LexRank for multi-document text summarization. Mihalcea and Tarau (2004) introduced TextRank for keyword and sentence extractions. Both LexRank and TextRank assume a fully connected, undirected graph, with text units as nodes and similarity as edges. After graph construction, both algorithms use a random walk on the graph to redistribute the node weights.

Many graph-based algorithms feature an evolutionary model, in which the graph changes over timesteps. An example is a citation network whose edges point backward in time: papers (usually) only reference older published works. References in old papers are static and are not updated. Simple models of Web growth are exemples of this: they model the chronological evolution of the Web in which a new webpage must be linked by an incoming edge in order to be publicly accessible and may embed links to existing webpages. These models differ in that they allow links in previously generated webpages to be updated or rewired. However, existing graph models for summarization – LexRank and TextRank – assume a static graph, and do not model how the input texts evolve. The central hypothesis of this paper is that modeling the evolution of input texts may improve the subsequent summarization process. Such a model may be based on human writing/reading process and should show how just composed/consumed units of text relate to previous ones. By applying this model over a series of timesteps, we obtain a representation of how information flows in the construction of the document set and leverage this to construct automatic summaries.

We first introduce and formalize our timestamped graph model in next section. In particular, our formalization subsumes previous works: we show in Section 3 that the graphs used by LexRank and TextRank are specific instances of our timestamped graph. In Section 4, we discuss how the resulting graphs are applied to automatic multi-document text summarization: by counting node in-degree or applying a random walk algorithm to smooth the information flow. We apply these models to create an extractive summarization program

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and apply it to the standard Document Understanding Conference (DUC) datasets. We discuss the resulting performance in Section 5.

2 Timestamped Graph

We believe that a proper evolutionary graph model of text should capture the writing and reading processes of humans. Although such human processes vary widely, when we limit ourselves to expository text, we find that both skilled writers and readers often follow conventional rhetorical styles (Endres-Niggemeyer, 1998; Liddy, 1991). In this work, we explore how a simple model of evolution affects graph construction and subsequent summarization. In this paper, our work is only exploratory and not meant to realistically model human processes and we believe that deep understanding and inference of rhetorical styles (Mann and Thompson, 1988) will improve the fidelity of our model. Nevertheless, a simple model is a good starting point.

We make two simple assumptions:

1: Writers write articles from the first sentence to the last;

2: Readers read articles from the first sentence to the last.

The assumptions suggest that we add sentences into the graph in chronological order: we add the first sentence, followed by the second sentence, and so forth, until the last sentence is added.

These assumptions are suitable in modeling the growth of individual documents. However when dealing with multi-document input (common in DUC), our assumptions do not lead to a straightforward model as to which sentences should appear in the graph before others. One simple way is to treat multi-document problems simply as multiple instances of the single document problem, which evolve in parallel. Thus, in multi-document graphs, we add a sentence from each document in the input set into the graph at each timestep. Our model introduces a skew variable to model this and other possible variations, which is detailed later.

The pseudocode in Figure 1 summarizes how we build a timestamped graph for multi-document input set. Informally, we build the graph iteratively, introducing new sentence(s) as node(s) in

Input:	**M**, a cluster of m documents relating to a common event;
Let:	**i** = index to sentences, initially 1; **G** = the timestamped graph, initially empty.
Step 1:	Add the **i**th sentence of all documents into **G**.
Step 2:	Let each existing sentence in **G** choose and connect to **one** other existing sentence in **G**. The chosen sentence must be sentence which has not been previously chosen by this sentence in previous iterations.
Step 3:	**if** there are no new sentences to add, **break;** **else** i++, goto Step 1.
Output:	**G**, a timestamped graph.

Figure 1: Pseudocode for a specific instance of a timestamped graph algorithm

the graph at each timestep. Next, all sentences in the graph pick other previously unconnected ones to draw a directed edge to. This process continues until all sentences are placed into the graph.

Figure 2 shows this graph building process in mid-growth, where documents are arranged in columns, with d_x represents the x^{th} document and s_y represents the y^{th} sentence of each document. The bottom shows the n^{th} sentences of all m documents being added simultaneously to the graph. Each new node can either connect to a node in the existing graph or one of the other m-1 new nodes. Each existing node can connect to another existing node or to one of the m newly-introduced nodes. Note that this model differs from the citation networks in such that new outgoing edges are introduced to old nodes, and differs from previous models for Web growth as it does not require new nodes to have incoming edges.

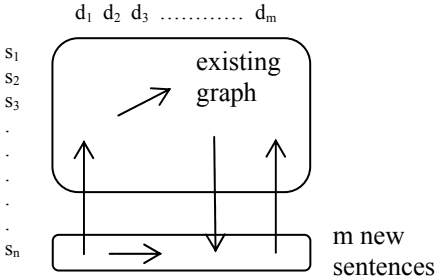
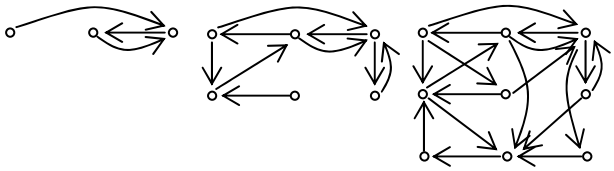


Figure 2: Snapshot of a timestamped graph.

Figure 3 shows an example of the graph building process over three timesteps, starting from an empty graph. Assume that we have three documents and each document has three sentences. Let d_xs_y indicate the y^{th} sentence in the x^{th} document. At timestep 1, sentences d_1s_1, d_2s_1 and d_3s_1 are

added to the graph. Three edges are introduced to the graph, in which the edges are chosen by some strategy; perhaps by choosing the candidate sentence by its maximum cosine similarity with the sentence under consideration. Let us say that this process connects $d_1s_1 \rightarrow d_3s_1$, $d_2s_1 \rightarrow d_3s_1$ and $d_3s_1 \rightarrow d_2s_1$. At timestep 2, sentences d_1s_2, d_2s_2 and d_3s_2 are added to the graph and six new edges are introduced to the graph. At timestep 3, sentences d_1s_3, d_2s_3 and d_3s_3 are added to the graph, and nine new edges are introduced.



(a) Timestep 1 (b) Timestep 2 (c) Timestep 3

Figure 3: An example of the growth of a timestamped graph.

The above illustration is just one instance of a timestamped graph with specific parameter settings. We generalize and formalize the timestamped graph algorithm as follows:

Definition: A timestamped graph algorithm *tsg*(*M*) is a 9-tuple (*d, e, u, f, σ, t, i, s, τ*) that specifies a resulting algorithm that takes as input the set of texts *M* and outputs a graph *G*, where:

d specifies the direction of the edges, $d \in \{f, b, u\}$;
e is the number of edges to add for each vertex in *G* at each timestep, $e \in \mathbb{Z}^+$;
u is 0 or 1, where 0 and 1 specifies unweighted and weighted edges, respectively;
f is the inter-document factor, $0 \leq f \leq 1$;
σ is a vertex selection function $\sigma(u, G)$ that takes in a vertex *u* and *G*, and chooses a vertex $v \in G$;
t is the type of text units, $t \in \{$*word, phrase, sentence, paragraph, document*$\}$;
i is the node increment factor, $i \in \mathbb{Z}^+$;
s is the skew degree, $s \geq -1$ and $s \in \mathbb{Z}$, where -1 represent free skew and 0 no skew;
τ is a document segmentation function $\tau(\bullet)$.

In the TSG model, the first set of parameters *d*, *e*, *u*, *f* deal with the properties of edges; *σ*, *t*, *i*, *s* deal with properties of nodes; finally, *τ* is a function that modifies input texts. We now discuss the first eight parameters; the relevance of *τ* will be expanded upon later in the paper.

2.1 Edge Settings

We can specify the direction of information flow by setting different *d* values. When a node v_1 chooses another node v_2 to connect to, we set *d* to *f* to represent a forward (outgoing) edge. We say that v_1 propagates some of its information into v_2. When letting a node v_1 choose another node v_2 to connect to v_1 itself, we set *d* to *b* to represent a backward (incoming) edge, and we say that v_1 receives some information from v_2. Similarly, $d = u$ specifies undirected edges in which information propagates in both directions. The larger amount of information a node receives from other nodes, the higher the importance of this node.

Our toy example in Figure 3 has small dimensions: three sentences for each of three documents. Experimental document clusters often have much larger dimensions. In DUC, clusters routinely contain over 25 documents, and the average length for documents can be as large as 50 sentences. In such cases, if we introduce one edge for each node at each timestep, the resulting graph is loosely connected. We let *e* be the number of outgoing edges for each sentence in the graph at each timestep. To introduce more edges into the graph, we increase *e*.

We can also incorporate unweighted or weighted edges into the graph by specifying the value of *u*. Unweighted edges are good when ranking algorithms based on in-degree of nodes are used. However, unlike links between webpages, edges between text units often have weights to indicate connection strength. In these cases, unweighted edges lose information and a weighted representation may be better, such as in cases where PageRank-like algorithms are used for ranking.

Edges can represent information flow from one node to another. We may prefer intra-document edges over inter-document edges, to model the intuition that information flows within the same document more likely than across documents. Thus we introduce an inter-document factor *f*, where $0 \leq f \leq 1$. When this feature is smaller than 1, we replace the weight *w* for inter-document edges by *fw*.

2.2 Node Settings

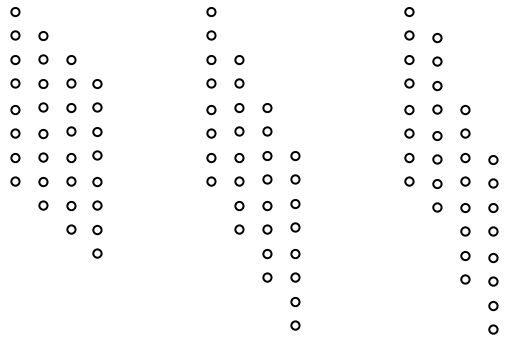
In Figure 1 Step 2, every existing node has a chance to choose another existing node to connect to. Which node to choose is decided by the selection strategy σ. One strategy is to choose the node with the highest similarity. There are many similarity functions to use, including token-based Jaccard similarity, cosine similarity, or more complex models such as concept links (Ye et al., 2005).

t controls the type of text unit that represents nodes. Depending on the application, text units can be words, phrases, sentences, paragraphs or even documents. In the task of automatic text summarization, systems are conveniently assessed by letting text units be sentences.

i controls the number of sentences entering the graph at every iteration. Certain models, such as LexRank, introduce all of the input sentences in one time step (i.e., $i = L_{max}$, where L_{max} is the maximum length of the input documents), completing the construction of *G* in one step. However, to model time evolution, *i* needs to be set to a value smaller than this.

Most relevant to our study is the skew parameter *s*. Up to now, the TSG models discussed all assume that authors start writing all documents in the input set at the same time. It is reflected by adding the first sentences of all documents simultaneously. However in reality, some documents are authored later than others, giving updates or reporting changes to events reported earlier. In DUC document clusters, news articles are typically taken from two or three different newswire sources. They report on a common event and thus follow a storyline. A news article usually gives summary about what have been reported in early articles, and gives updates or changes on the same event.

To model this, we arrange the documents in accordance with the publishing time of the documents. The earliest document is assigned to column 1, the second earliest document to column 2, and so forth, until the latest document is assigned to the last column. The graph construction process is the same as before, except that we delay adding the first sentences of later documents until a proper iteration, governed by *s*. With $s = 1$, we delay the addition of the first sentence of column 2 until the second timestep, and delay the addition of the first sentence of column 3 until the third timestep. The resulting timestamped graph is skewed by 1 timestep (Figure 4 (a)). We can increase the skew degree *s* if the time intervals between publishing time of documents are large. Figure 4 (b) shows a timestamped graph skewed by 2 timesteps. We can also skew a graph freely by setting *s* to -1. When we start to add the first sentence d_is_1 of a document d_i, we check whether there are existing sentences in the graph that want to connect to d_is_1 (i.e., that $\sigma(\bullet, G) = d_is_1$). If there is, we add d_is_1 to the graph; else we delay the addition and reassess again in next timestep. The result is a freely skewed graph (Figure 4 (c)). In Figure 4 (c), we start adding the first sentences of documents d_2 to d_4 at timesteps 2, 5 and 7, respectively. At timestep 1, d_1s_1 is added into the graph. At timestep 2, an existing node (d_1s_1 in this case) wants to connect to d_2s_1, so d_2s_1 is added. d_3s_1 is added at timestep 5 as no existing node wants to connect to d_3s_1 until timestep 5. Similarly, d_4s_1 is added until some nodes choose to connect to it at timestep 7. Notice that we hide edges in Figure 4 for clarity.



(a) Skewed by 1 (b) Skewed by 2 (c) Freely skewed

Figure 4: Skewing the graphs. Edges are hidden for clarity. For each graph, the leftmost column is the earliest document. Documents are then chronologically ordered, with the rightmost one being the latest.

3 Comparison and Properties of TSG

The TSG representation generalizes many possible specific algorithm configurations. As such, it is natural that previous works can be cast as specific instances of a TSG. For example, we can succinctly represent the algorithm used in the running example in Section 2 as the tuple (*f, 1, 0, 1, max-cosine-based, sentence, 1, 0, null*). LexRank and TextRank can also be cast as TSGs: (*u, N, 1, 1, cosine-based, sentence,* L_{max}*, 0, null*) and (*u, L, 1, 1, modified-co-occurrence-based, sentence, L, 0,*

null). As LexRank is applied in multi-document summarizations, *e* is set to the total number of sentences in the cluster, N, and *i* is set to the maximum document length in the cluster, L_{max}. TextRank is applied in single-document summarization, so both its *e* and *i* are set to the length of the input document, *L*. This compact notation emphasizes the salient differences between these two algorithm variants: namely that, *e*, σ and *i*.

Despite all of these possible variations, all timestamped graphs have two important features, regardless of their specific parameter settings. First, nodes that were added early have more chosen edges than nodes added later, as visible in Figure 3 (c). If forward edges (*d* = *f*) represent information flow from one node to another, we can say that more information is flowing from these early nodes to the rest of the graph. The intuition for this is that, during the writing process of articles, early sentences have a greater influence to the development of the articles' ideas; similarly, during the reading process, sentences that appear early contribute more to the understanding of the articles.

The fact that early nodes stay in the graph for a longer time leads to the second feature: early nodes may attract more edges from other nodes, as they have larger chance to be chosen and connected by other nodes. This is also intuitive for forward edges (*d* = *f*): during the writing process, later sentences refer back to early sentences more often than vice versa; and during the reading process, readers tend to re-read early sentences when they are not able to understand the current sentence.

4 Random Walk

Once a timestamped graph is built, we want to compute an importance score for each node. These scores are then used to determine which nodes (sentences) are the most important to extract summaries from. The graph *G* shows how information flows from node to node, but we have yet to let the information actually flow. One method to do this is to use the in-degree of each node as the score. However, most graph algorithms now use an iterative method that allows the weights of the nodes redistribute until stability is reached. One method for this is by applying a random walk, used in PageRank (Brin and Page, 1998). In PageRank the Web is treated as a graph of webpages connected by links. It assumes users start from a random webpage, moving from page to page by following the links. Each user follows the links at random until he gets "bored" and jumps to a random webpage. The probability of a user visiting a webpage is then proportional to its PageRank score. PageRank can be iteratively computed by:

$$PR(u) = \frac{\alpha}{N} + (1-\alpha) \sum_{v \in In(u)} \frac{1}{|Out(v)|} PR(v) \quad (1)$$

where *N* is the total number of nodes in the graph, *In*(*u*) is the set of nodes that point to *u*, and *Out*(*u*) is the set of nodes that node *u* points to. α is a damping factor that can be set between 0 and 1, which has the role of integrating into the model the probability of jumping from a given node to another random node in the graph. In the context of web surfing, a user either clicks on a link on the current page at random with probability 1 - α, or opens a completely new random page with probability α.

Equation 1 does not take into consideration the weights of edges, as the original PageRank definition assumes hyperlinks are unweighted. Thus we can use Equation 1 to rank nodes for an unweighted timestamped graph. To integrate edge weights into the graph, we modify Eq. 1, yielding:

$$PR(u) = \frac{\alpha}{N} + (1-\alpha) \sum_{v \in In(u)} \frac{w_{vu}}{\sum_{x \in Out(v)} w_{vx}} PR(v) \quad (2)$$

where W_{vu} represents the weight of the edge pointing from *v* to *u*.

As we may have a query for each document cluster, we also wish to take queries into consideration in ranking the nodes. Haveliwala (2003) introduces a topic-sensitive PageRank computation. Equations 1 and 2 assume a random walker jumps from the current node to a random node with probability α. The key to creating topic-sensitive PageRank is that we can bias the computation by restricting the user to jump only to a random node which has non-zero similarity with the query. Otterbacher et al. (2005) gives an equation for topic-sensitive and weighted PageRank as:

$$PR(u) = \alpha \frac{sim(u,Q)}{\sum_{y \in S} sim(y,Q)} + (1-\alpha) \sum_{v \in In(u)} \frac{w_{vu}}{\sum_{x \in Out(v)} w_{vx}} PR(v) \quad (3)$$

where S is the set of all nodes in the graph, and $sim(u, Q)$ is the similarity score between node u and the query Q.

5 Experiments and Results

We have generalized and formalized evolutionary timestamped graph model. We want to apply it on automatic text summarization to confirm that these evolutionary models help in extracting important sentences. However, the parameter space is too large to test all possible TSG algorithms. We conduct experiments to focus on the following research questions that relating to 3 TSG parameters - e, u and s, and the topic-sensitivity of PageRank.

Q1: Do different e values affect the summarization process?

Q2: How do topic-sensitivity and edge weighting perform in running PageRank?

Q3: How does skewing the graph affect information flow in the graph?

The datasets we use are DUC 2005 and 2006. These datasets both consist of 50 document clusters. Each cluster consists of 25 news articles which are taken from two or three different newswire sources and are relating to a common event, and a query which contains a topic for the cluster and a sequence of statements or questions. The first three experiments are run on DUC 2006, and the last experiment is run on DUC 2005.

In the first experiment, we analyze how e, the number of chosen edges for each node at each timestep, affects the performance, with other parameters fixed. Specifically the TSG algorithm we use is the tuple (*f, e, 1, 1, max-cosine-based, sentence, 1, 0, null*), where e is being tested for different values. The node selection function *max-cosine-based* takes in a sentence s and the current graph G, computes the TFIDF-based cosine similarities between s and other sentences in G, and connects s to e sentence(s) that has(have) the highest cosine score(s) and is(are) not yet chosen by s in previous iterations. We run topic-sensitive PageRank with damping factor α set to 0.5 on the graphs. Figures 5 (a)-(b) shows the ROUGE-1 and ROUGE-2 scores with e set to 1, 2, 3, 4, 5, 6, 7, 10, 15, 20 and N, where N is the total number of sentences in the cluster. We succinctly represent LexRank graphs by the tuple (*u, N, 1, 1, cosine-based, sentence, L_{max}, 0, null*) in Section 3; it can also be represented by a slightly different tuple (*f, N, 1, 1, max-cosine-based, sentence, 1, 0, null*). It differs from the first representation in that we iteratively add 1 sentence for each document in each timestep and let all nodes in the current graph connect to every other node in the graph. In this experiment, when e is set to N, the timestamped graph is equivalent to a LexRank graph. We do not use any reranker in this experiment.

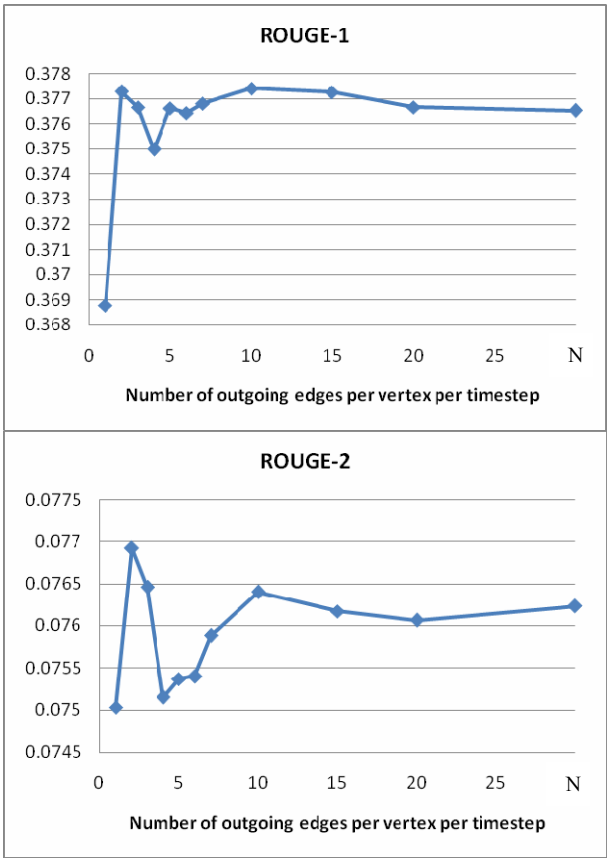


Figure 5: (a) ROUGE-1 and (b) ROUGE-2 scores for timestamped graphs with different e settings. N is the total number of sentences in the cluster.

The results allow us to make several observations. First, when e = 2, the system gives the best performance, with ROUGE-1 score 0.37728 and ROUGE-2 score 0.07692. Some values of e give better scores than LexRank graph configuration, in which e = N. Second, the system gives very bad performance when e = 1. This is because when e is set to 1, the graph is too loosely connected and is not suitable to apply random walk on it. Third, the system gives similar performance when e is set

greater than 10. The reason for this is that the higher values of *e* make the graph converge to a fully connected graph so that the performance starts to converge and display less variability.

We run a second experiment to analyze how topic-sensitivity and edge weighting affect the system performance. We use concept links (Ye et al., 2005) as the similarity function and a MMR reranker to remove redundancy. Table 1 shows the results. We observe that both topic-sensitive PageRank and weighted edges perform better than generic PageRank on unweighted timestamped graphs. When topic-sensitivity and edge weighting are both set to true, the system gives the best performance.

Topic-sensitive	Weighted edges	ROUGE-1	ROUGE-2
No	No	0.39358	0.07690
Yes	No	0.39443	0.07838
No	Yes	0.39823	0.08072
Yes	Yes	0.39845	0.08282

Table 1: ROUGE-1 and ROUGE-2 scores for different combinations of topic-sensitivity and edge weighting(u) settings.

To evaluate how skew degree *s* affects summarization performance, we use the parameter setting from the first experiment, with *e* fixed to 1. Specifically, we use the tuple (*f, 1, 1, 1, concept-link-based, sentence, 1, s, null*), with *s* set to 0, 1 and 2. Table 2 gives the evaluation results. We observe that $s = 1$ gives the best ROUGE-1 and ROUGE-2 scores. Compared to the system without skewing ($s = 0$), $s = 2$ gives slightly better ROUGE-1 score but worse ROUGE-2 score. The reason for this is that $s = 2$ introduces a delay interval that is too large. We expect that a freely skewed graph ($s = -1$) will give more reasonable delay intervals.

Skew degree	ROUGE-1	ROUGE-2
0	0.36982	0.07580
1	0.37268	0.07682
2	0.36998	0.07489

Table 2: ROUGE-1 and ROUGE-2 scores for different skew degrees.

We tune the system using different combinations of parameters, and the TSG algorithm with tuple (*f, 1, 1, 1, concept-link-based, sentence, 1, 0, null*) gives the best scores. We run this TSG algorithm with topic-sensitive PageRank and MMR reranker on DUC 2005 dataset. The results show that our system ranks third in both ROUGE-2 and ROUGE-SU4 scores.

Rank	System	ROUGE-2	System	ROUGE-SU4
1	15	0.0725	15	0.1316
2	17	0.0717	17	0.1297
3	**TSG**	**0.0712**	**TSG**	**0.1285**
4	10	0.0698	8	0.1279
5	8	0.0696	4	0.1277

Table 3: top ROUGE-2 and ROUGE-SU4 scores in DUC 2005. TSG is our system.

6 Discussion

A closer inspection of the experimental clusters reveals one problem. Clusters that consist of documents that are of similar lengths tend to perform better than those that contain extremely long documents. The reason is that a very long document introduces too many edges into the graph. Ideally we want to have documents with similar lengths in a cluster. One solution to this is that we split long documents into shorter documents with appropriate lengths. We introduce the last parameter in the formal definition of timestamped graphs, τ, which is a document segmentation function $\tau(\bullet)$. $\tau(M)$ takes in as input a set of documents M, applies segmentation on long documents to split them into shorter documents, and output a set of documents with similar lengths, M'. Slightly better results are achieved when a segmentation function is applied. One shortcoming of applying $\tau(\bullet)$ is that when a document is split into two shorter ones, the early sentences of the second half now come before the later sentences of the first half, and this may introduce inconsistencies in our representation: early sentences of the second half contribute more into later sentences of the first half than the vice versa.

7 Related Works

Dorogovtsev and Mendes (2001) suggest schemes of the growth of citation networks and the Web, which are similar to the construction process of timestamped graphs.

Erkan and Radev (2004) proposed LexRank to define sentence importance based on graph-based centrality ranking of sentences. They construct a similarity graph where the cosine similarity of each pair of sentences is computed. They introduce three different methods for computing centrality in

similarity graphs. Degree centrality is defined as the in-degree of vertices after removing edges which have cosine similarity below a pre-defined threshold. LexRank with threshold is the second method that applies random walk on an unweighted similarity graph after removing edges below a pre-defined threshold. Continuous LexRank is the last method that applies random walk on a fully connected, weighted similarity graph. LexRank has been applied on multi-document text summarization task in DUC 2004, and topic-sensitive LexRank has been applied on the same task in DUC 2006.

Mihalcea and Tarau (2004) independently proposed another similar graph-based random walk model, TextRank. TextRank is applied on keyword extraction and single-document summarization. Mihalcea, Tarau and Figa (2004) later applied PageRank to word sense disambiguation.

8 Conclusion

We have proposed a timestamped graph model which is motivated by human writing and reading processes. We believe that a suitable evolutionary text graph which changes over timesteps captures how information propagates in the text graph. Experimental results on the multi-document text summarization task of DUC 2006 showed that when *e* is set to 2 with other parameters fixed, or when *s* is set to 1 with other parameters fixed, the graph gives the best performance. It also showed that topic-sensitive PageRank and weighted edges improve summarization process. This work also unifies representations of graph-based summarization, including LexRank and TextRank, modeling these prior works as specific instances of timestamped graphs.

We are currently looking further on skewed timestamped graphs. Particularly we want to look at how a freely skewed graph propagates information. We are also analyzing in-degree distribution of timestamped graphs.

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