

Spoken Lecture Summarization by Random Walk over a Graph Constructed with Automatically Extracted Key Terms

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Outline

- o Introduction
- o Graph-based summarization approach
 - A spoken document is transformed into a graph structure
 - Nodes: sentences in a spoken document
 - Edge weight: topical similarities of sentences
 - Random walk is used to select indicative sentences
 - all sentences in a document can be jointly considered
- o Experiments
- o Conclusion

Introduction –

Extractive Summarization (1/2)

- o Extractive speech summarization
 - o Select the indicative sentences in a spoken document
 - o Cascade the sentences to form a summary
 - o The number of sentences selected as summary is decided by a predefined ratio

Introduction –

Extractive Summarization (2/2)

- Each sentence S in a spoken document d is given an *importance score* $I(S,d)$
- Select the indicative sentences based on $I(S,d)$

sentence

term

$$S = t_1 t_2 \dots t_i \dots t_n$$

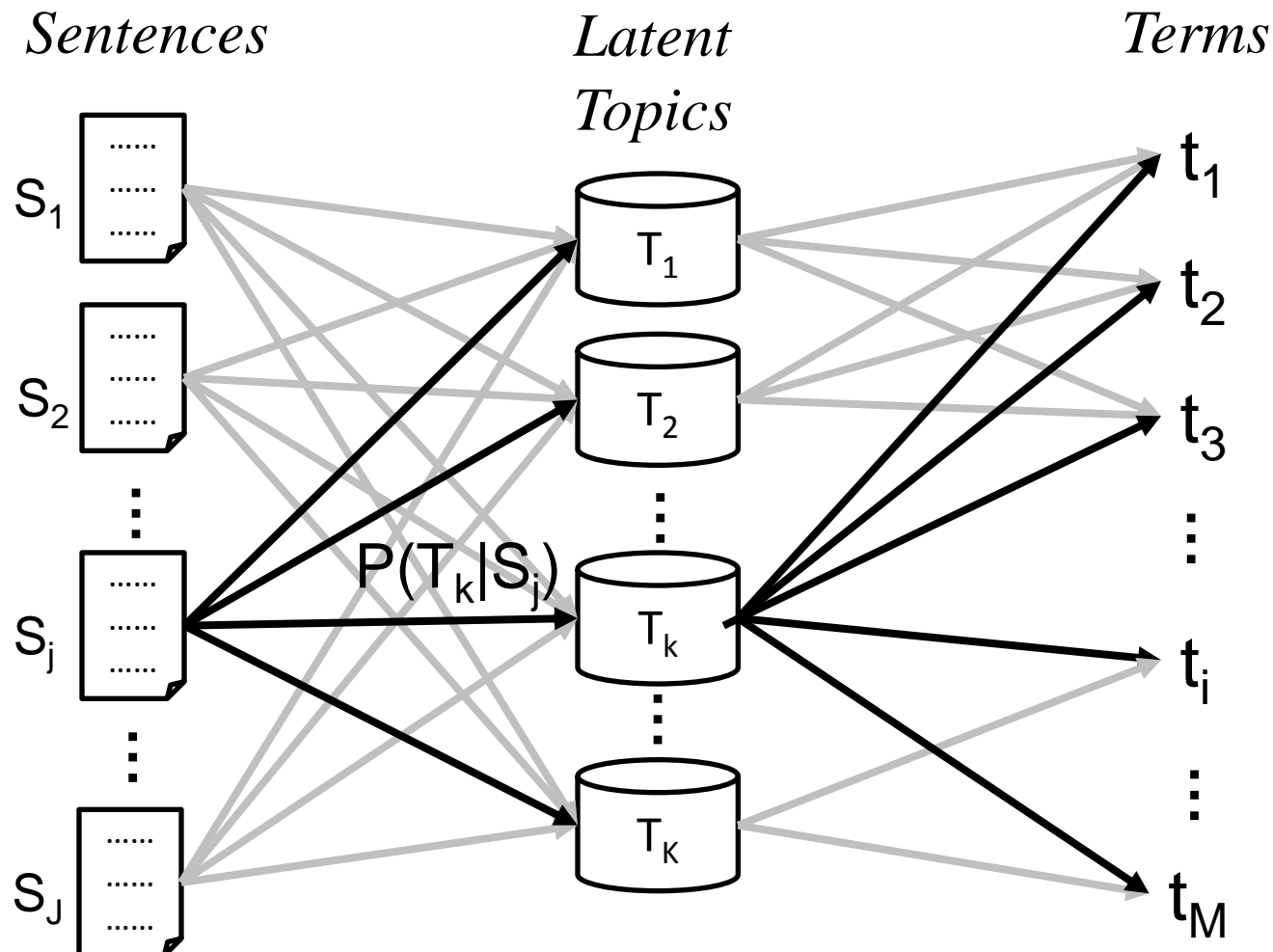
↓

$$I(S, d) = \sum_{i=1}^n [s(t_i, d) \dots] + \dots$$

Importance score

term statistical measure

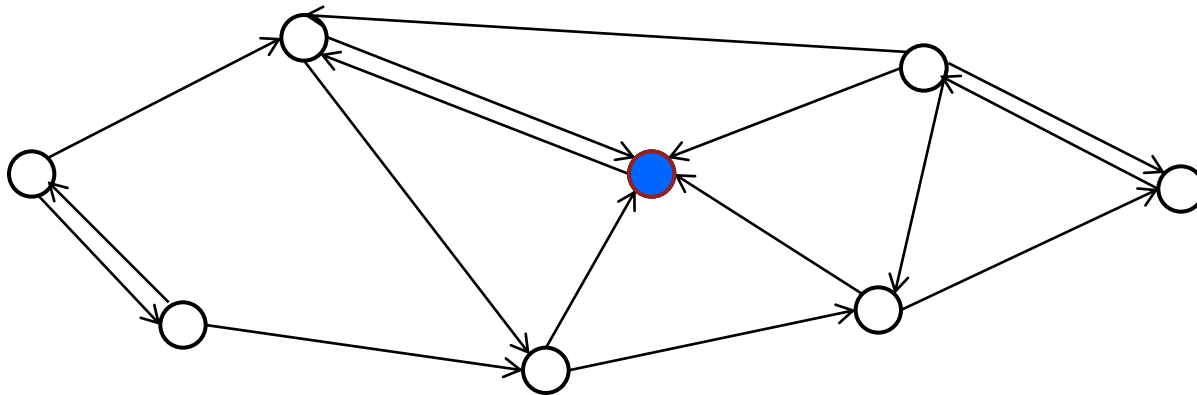
Introduction – PLSA



$P(T_k | S_j)$: weight of latent topic T_k for sentence S_j

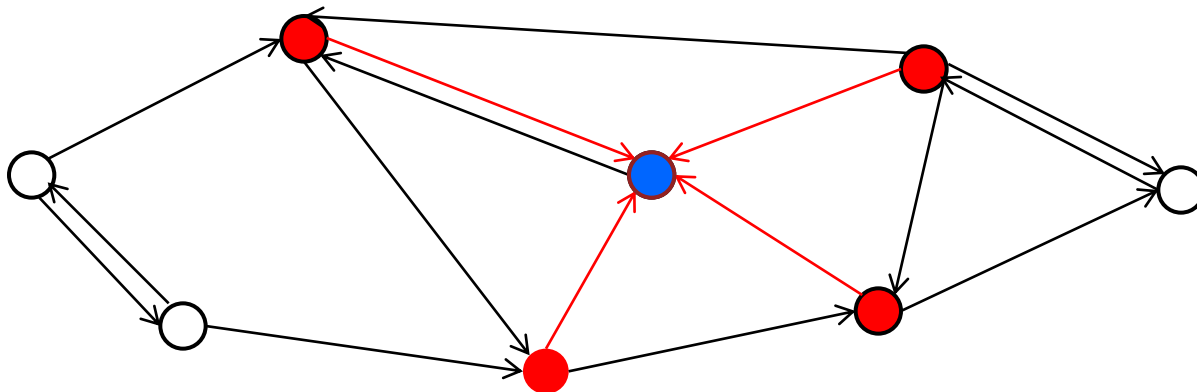
Proposed Approach (1/2)

- Basic idea
 - Not only the sentences with high importance score based on statistical measure should be considered as indicative sentence



Proposed Approach (1/2)

- Basic idea
 - Not only the sentences with high importance score based on statistical measure should be considered as indicative sentence
 - But the sentences topically similar to the indicative sentences should also be considered as indicative

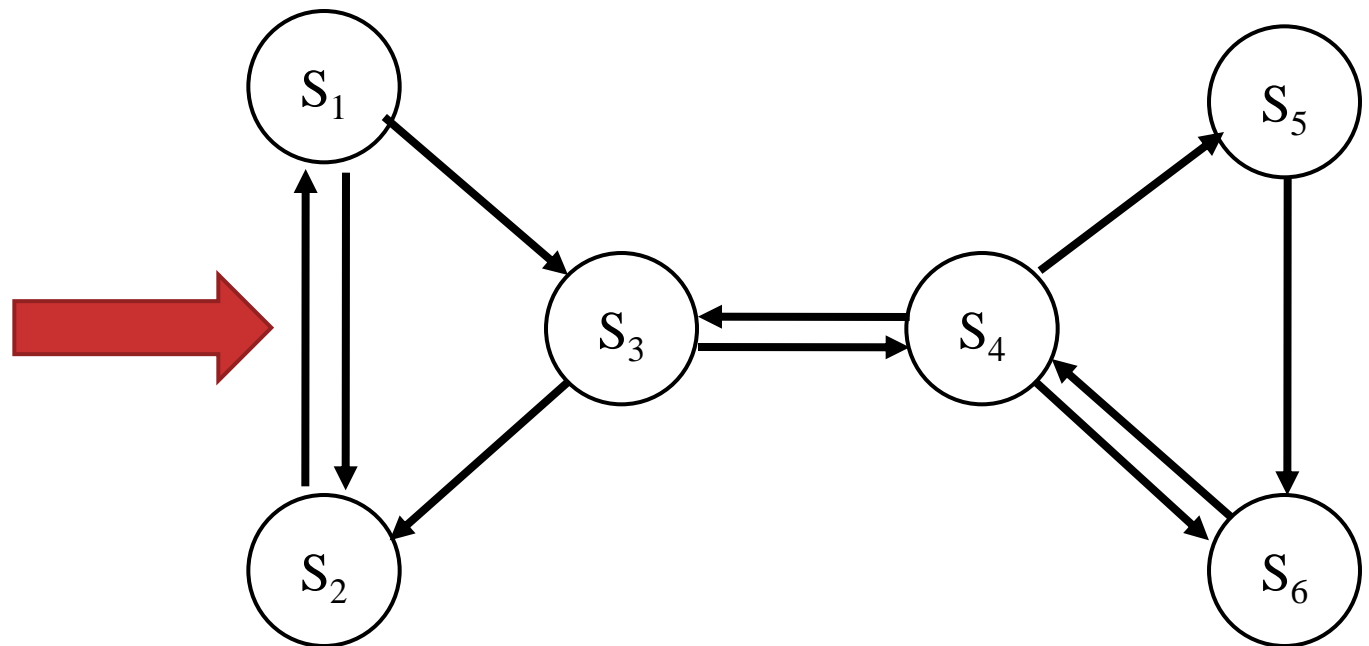
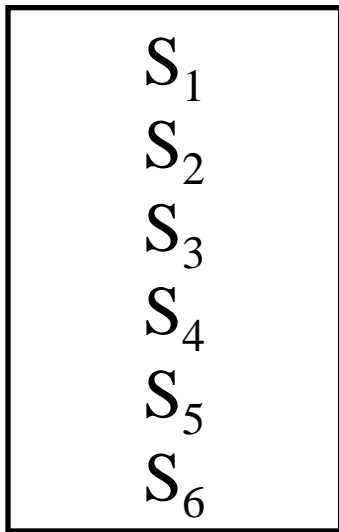


Proposed Approach (2/2)

- Graph-based approach
 - Sentences in a spoken document are nodes on a graph, and topical similarities of sentences are weights of edges.
 - Use random walk to obtain new scores for summary selection
 - → all sentences in the document can be jointly considered rather than individually.

Graph Construction (1/2)

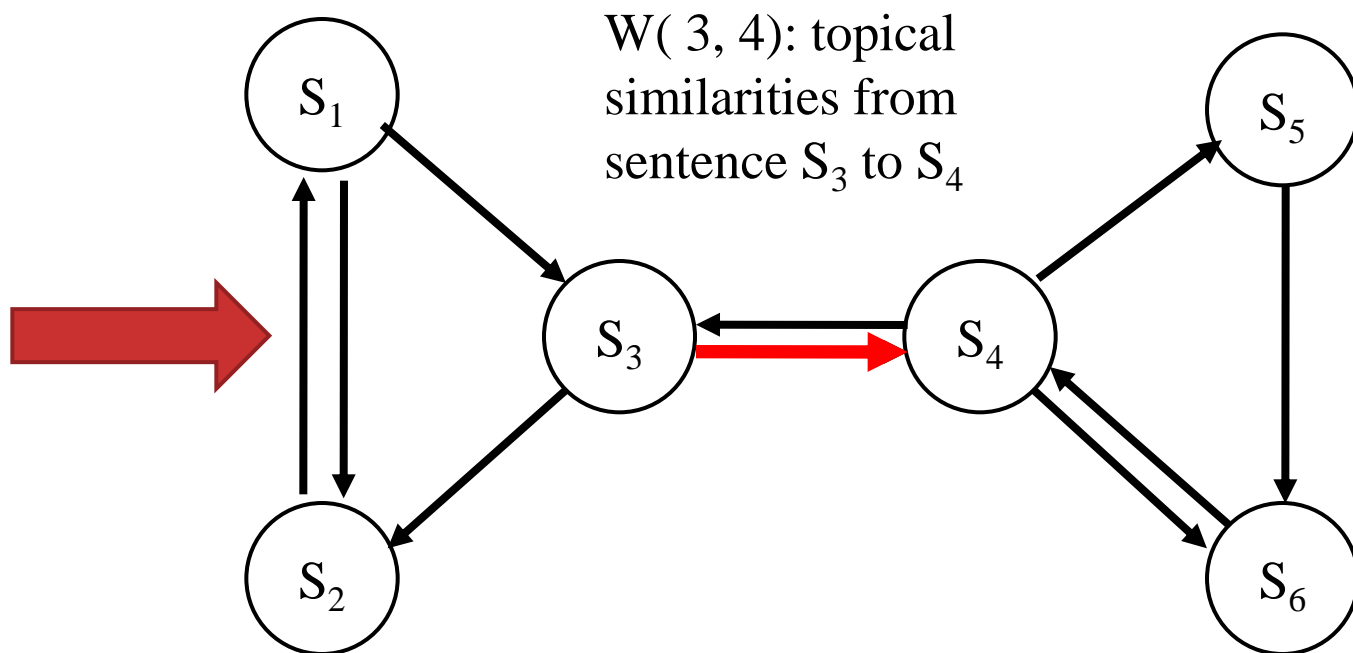
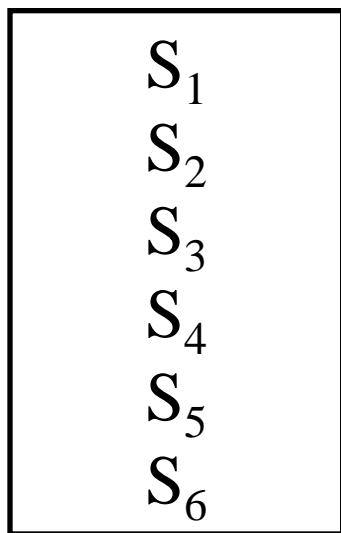
Spoken
Document d



Each sentence S_i in the spoken document d is a node on the graph.

Graph Construction (1/2)

Spoken
Document d



$W(i, j) (S_i \rightarrow S_j)$:

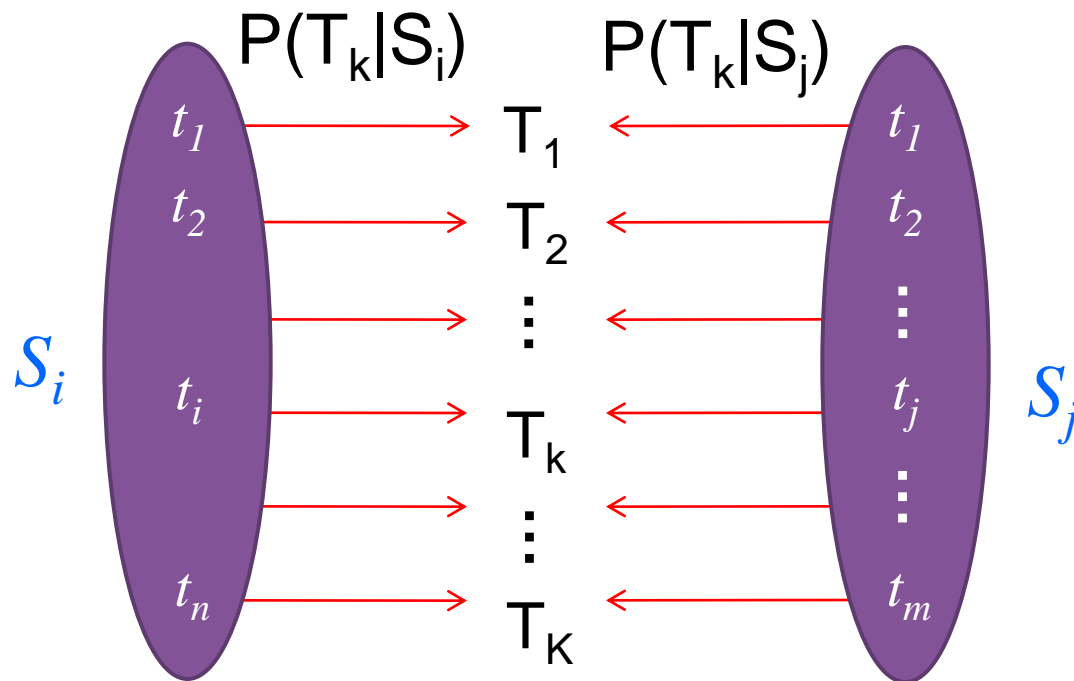
Topical similarity from sentence S_i to S_j

(based on *PLSA latent topics* of sentences)

Graph Construction (2/2)

- Topical Similarities

- Topical Similarity from sentences S_i to S_j
 - Edge weight $W(i, j)$ (sentence $S_i \rightarrow$ sentence S_j)



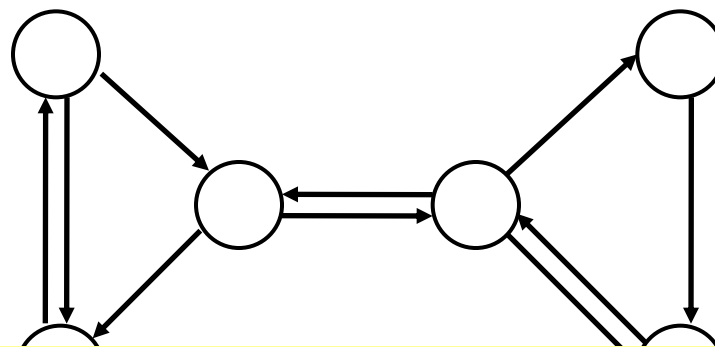
◆ $W(i, j)$: evaluated by the latent topic similarities of sentences S_i to S_j based on PLSA model

Mathematical Formulation

Find a set of new scores based on graph structure

$\{G(i)$ for each sentence S_i in document $d\}$ which satisfies

$$G(i) = (1 - \alpha)I(S_i, d) + \alpha \sum_{S_j \in in(i)} G(j) \hat{W}(j, i)$$



- ◆ $G(i)$ for sentence S_i would be a new importance score for summary selection

Mathematical Formulation

Find a set of new scores based on graph structure

$\{G(i)$ for each sentence S_i in document $d\}$ which satisfies

$$G(i) = (1 - \alpha) I(S_i, d) + \alpha \sum_{S_j \in in(i)} G(j) \hat{W}(j, i)$$

The original importance score of node S_i
(weighted by $1 - \alpha$)

Scores propagate from other nodes to node S_i
(weighted by α)

Mathematical Formulation

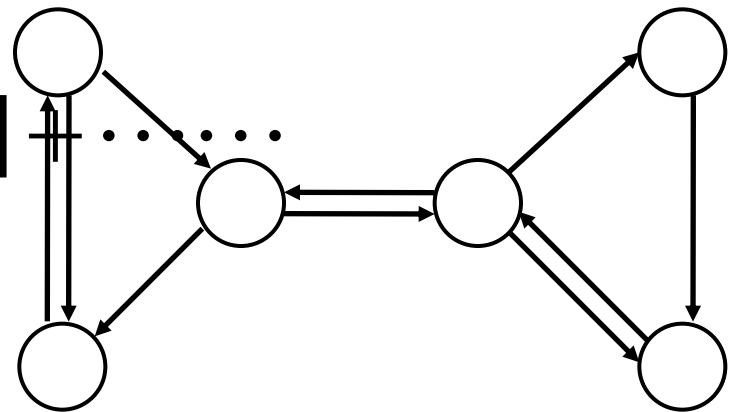
Find a set of new scores based on graph structure

$\{G(i)$ for each sentence S_i in document $d\}$ which satisfies

$$G(i) = (1 - \alpha) \mathbf{I}(S_i, d) + \alpha \sum_{S_j \in \text{in}(i)} G(j) \hat{W}(j, i)$$

$$I(S, d) = \sum_{i=1}^n [s(t_i, d) \dots \dots \dots]$$

Importance score term statistical measure

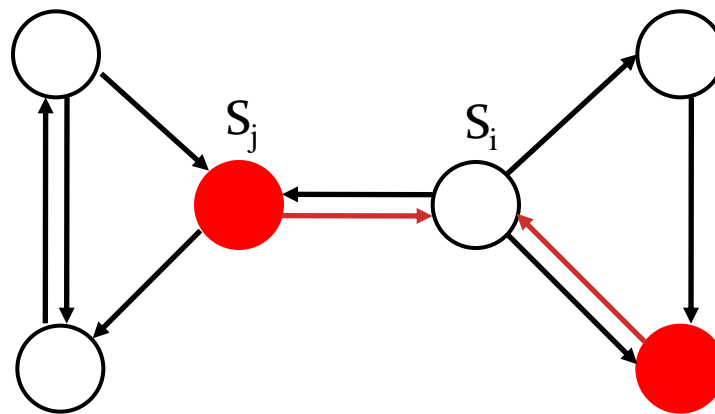


Mathematical Formulation

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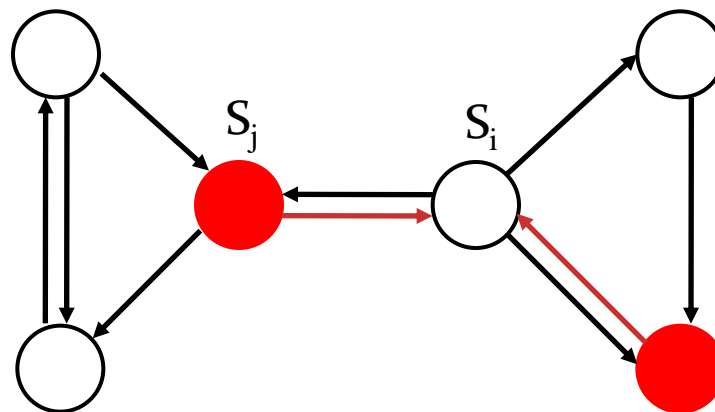


Mathematical Formulation

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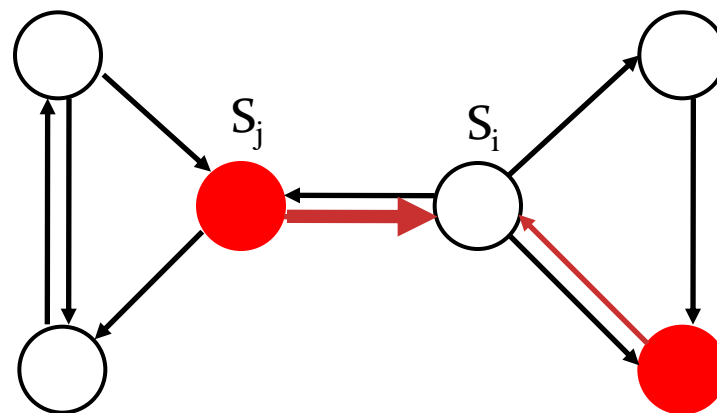
Mathematical Formulation

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$$G(i) = (1 - \alpha)I(S_i, d) + \alpha \sum_{S_j \in in(i)} G(j) \hat{W}(j, i)$$

$$\hat{W}(j, i) = \frac{W(j, i)}{\sum_{S_k \in out(j)} W(j, k)}$$



Mathematical Formulation

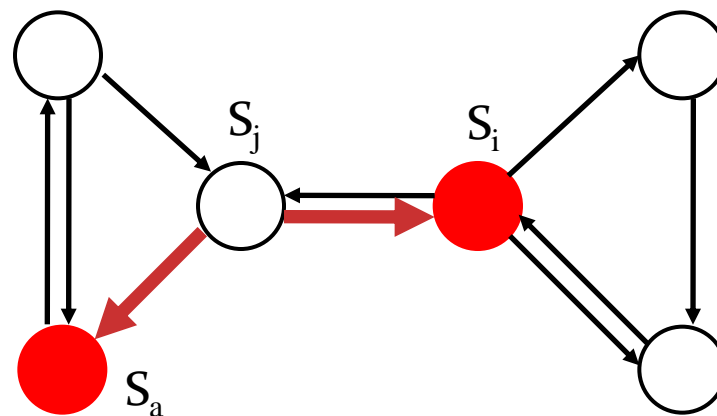
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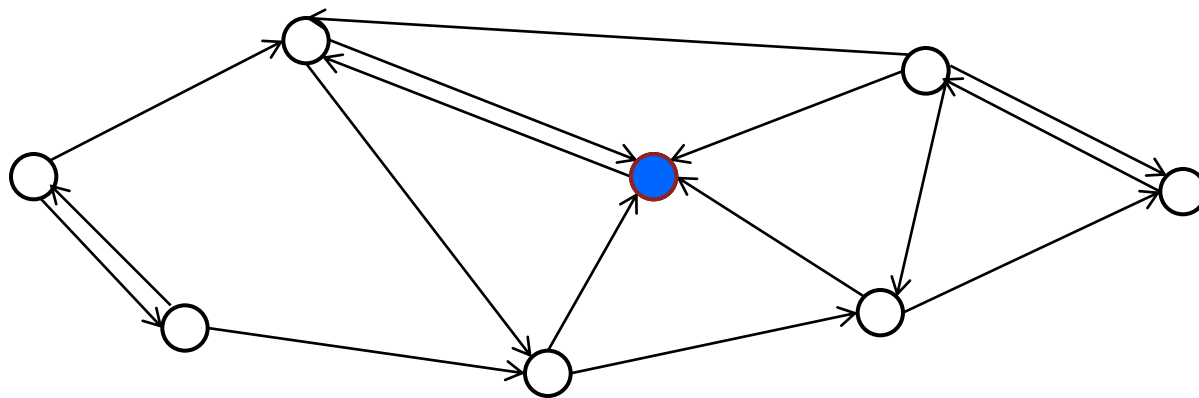
$$\hat{W}(j, i) = \frac{W(j, i)}{\sum_{S_k \in out(j)} W(j, k)}$$

The scores propagate from a node to all other nodes sums to unity.



Mathematical Formulation

$$G(i) = (1 - \alpha)I(S_i, d) + \alpha \sum_{S_j \in in(i)} G(j) \hat{W}(j, i)$$

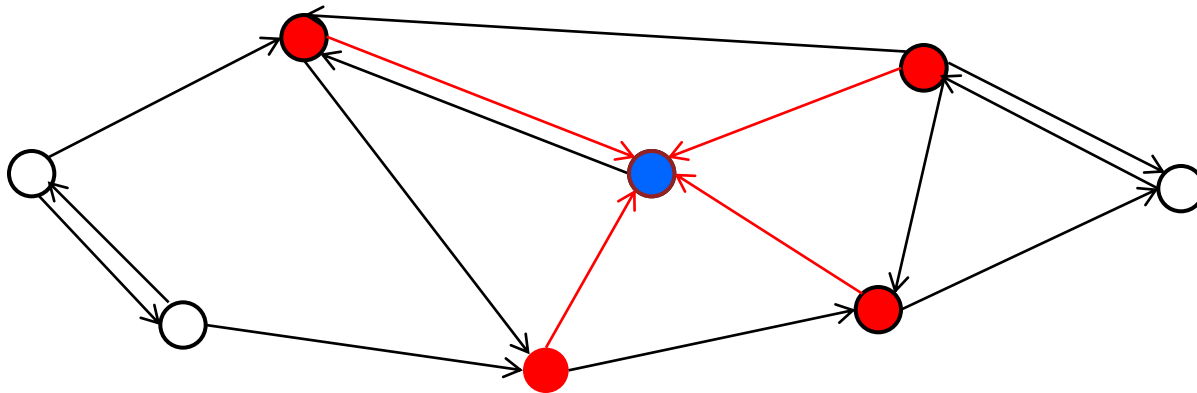


◆ $G(i)$ can obtain higher score when

- 1) $I(S_i, d)$ is high.
- 2) More sentences topically similar to S_i

Mathematical Formulation

$$G(i) = (1 - \alpha)I(S_i, d) + \alpha \sum_{S_j \in \text{in}(i)} G(j) \hat{W}(j, i)$$

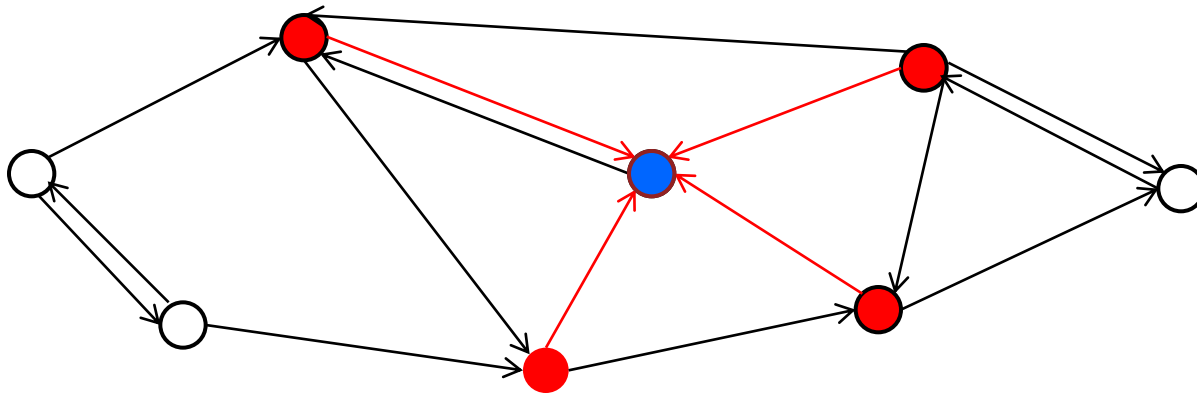


◆ $G(i)$ can obtain higher score when

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Mathematical Formulation

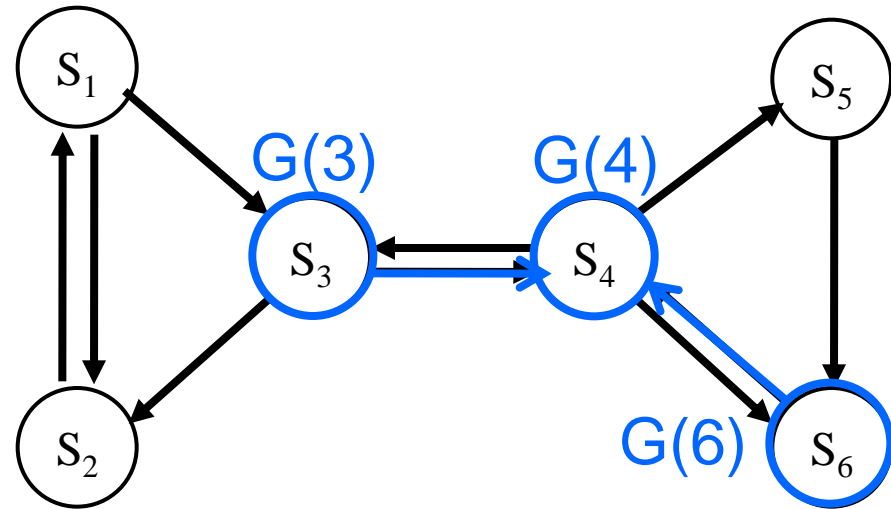
$$G(i) = (1 - \alpha)I(S_i, d) + \alpha \sum_{S_j \in \text{in}(i)} G(j) \hat{W}(j, i)$$



- All sentences in the documents are considered jointly
- Rather than individually

Mathematical Formulation – an Example

Find $G(1)$, $G(2)$, $G(3)$, $G(4)$, $G(5)$, $G(6)$ such that



$$G(4) = (1 - \alpha)I(S_4, d) + \alpha G(6) \hat{W}(6,4) + \alpha G(3) \hat{W}(3,4)$$

Mathematical Formulation – Equations to be solved

Find $G(1)$, $G(2)$, $G(3)$, $G(4)$,
 $G(5)$, $G(6)$ such that

$$G(1) = (1 - \alpha)I(S_1, d) + \alpha G(2)\hat{W}(2,1)$$

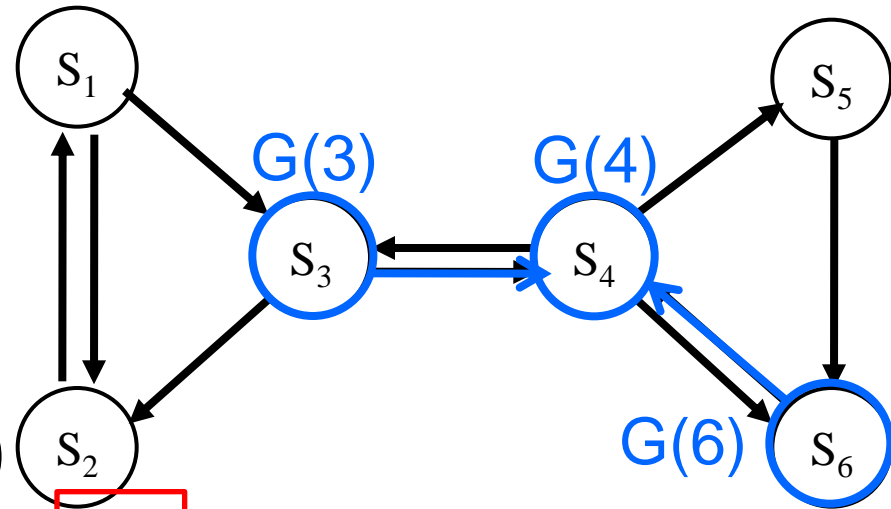
$$G(2) = (1 - \alpha)I(S_2, d) + \alpha G(3)\hat{W}(3,2)$$

$$G(3) = (1 - \alpha)I(S_3, d) + \alpha G(1)\hat{W}(1,3) + \alpha G(4)\hat{W}(4,3)$$

$$G(4) = (1 - \alpha)I(S_4, d) + \alpha G(6)\hat{W}(6,4) + \alpha G(3)\hat{W}(3,4)$$

$$G(5) = (1 - \alpha)I(S_5, d) + \alpha G(4)\hat{W}(4,5)$$

$$G(6) = (1 - \alpha)I(S_6, d) + \alpha G(4)\hat{W}(4,6) + \alpha G(5)\hat{W}(5,6)$$

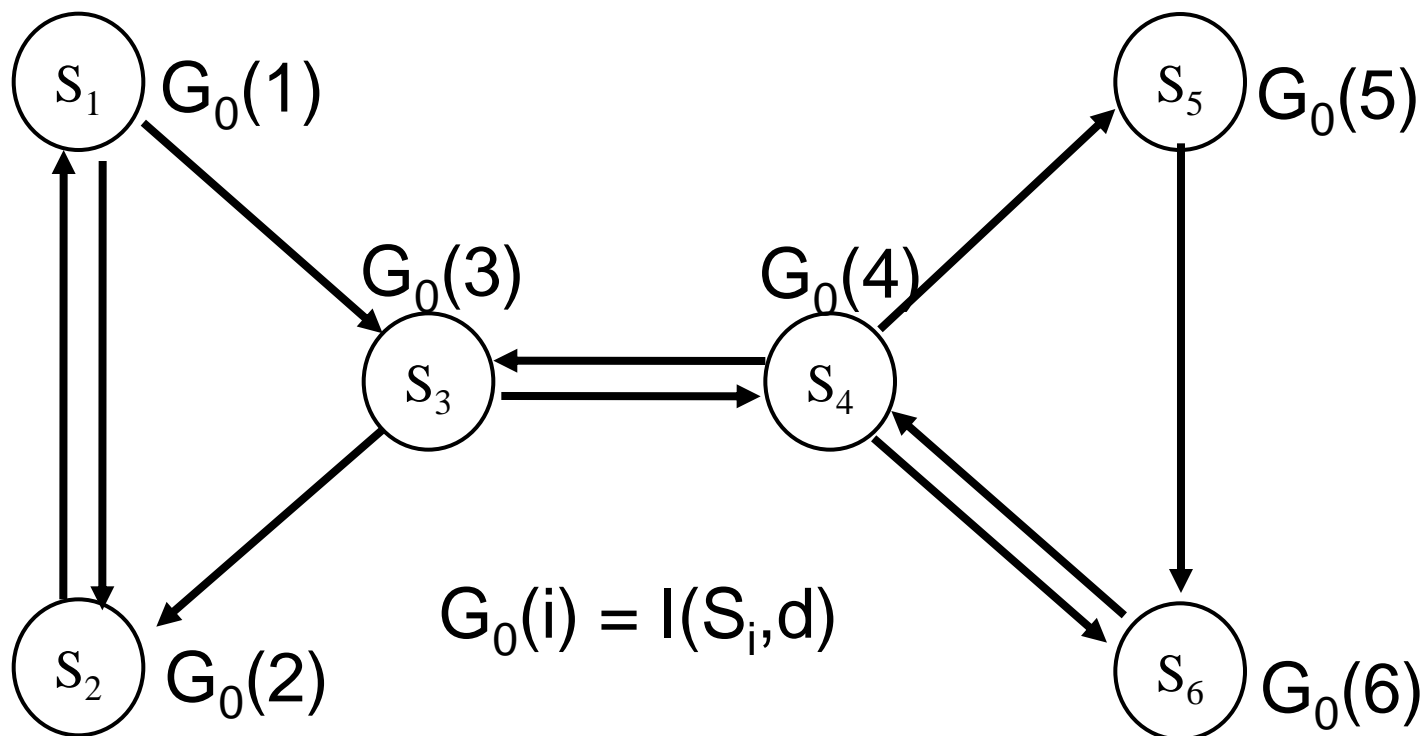


◆ How to solve these equations to obtain $G(1)$, $G(2)$, $G(6)$?

➤ solve the problem iteratively (random walk)

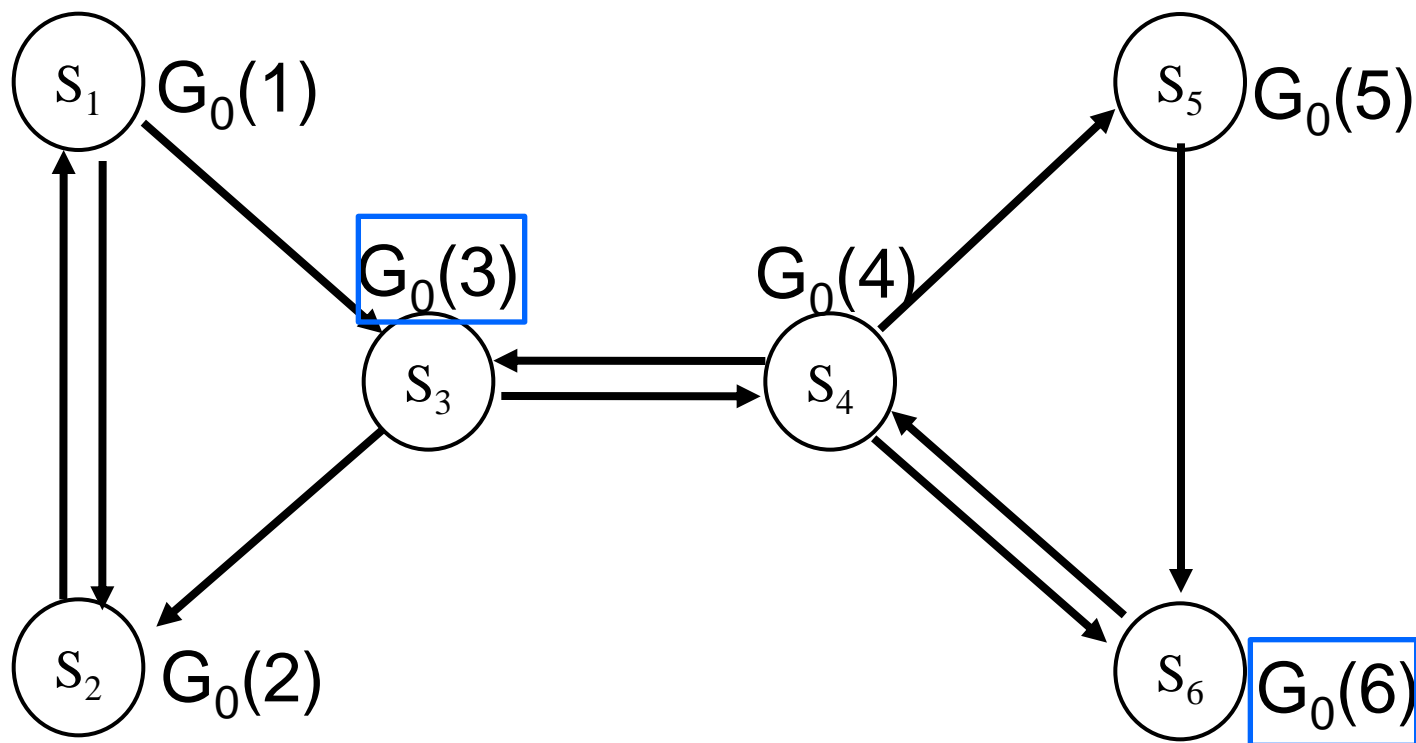
Random Walk Solution

◆ Each sentence is assigned an initial value $G_0(i)$



Random Walk Solution

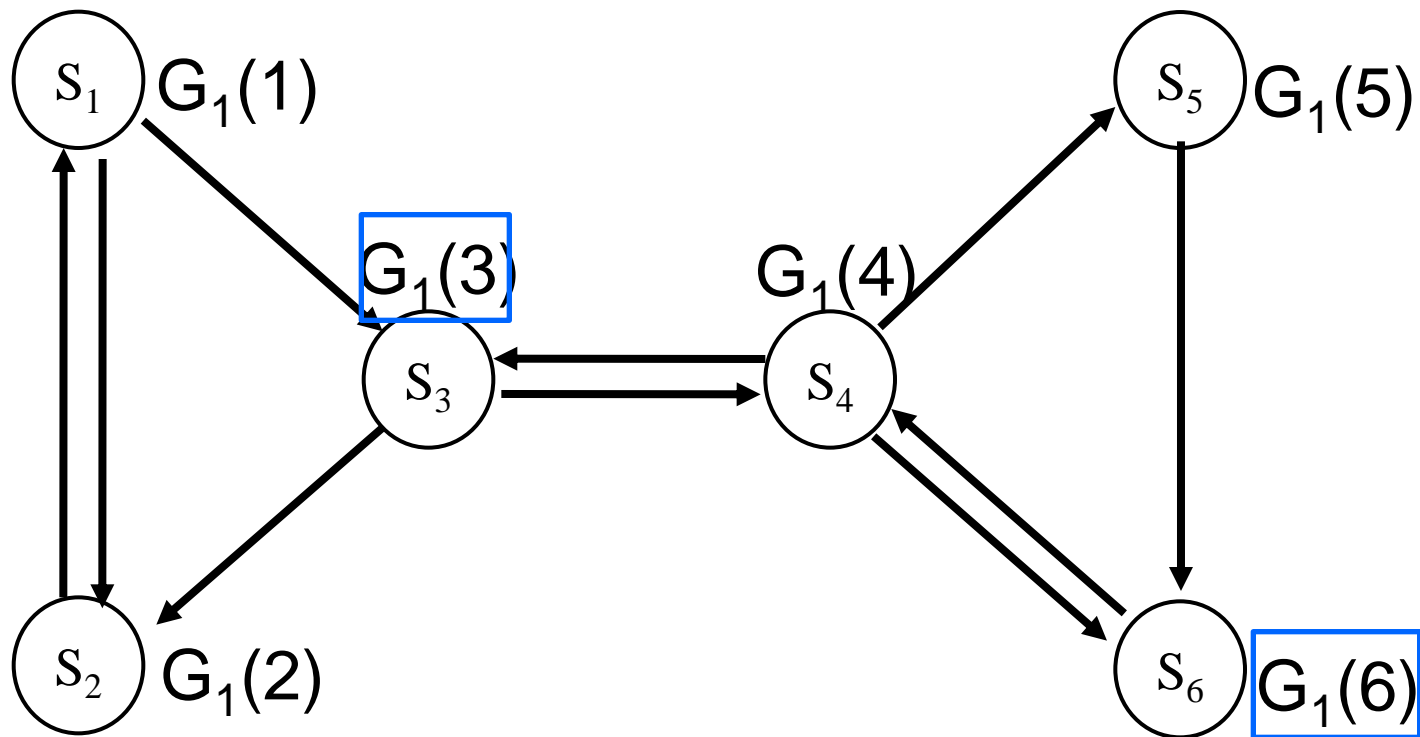
- ◆ Update the score for each sentence



$$G_1(4) = (1 - \alpha) I(S_4, d) + \alpha G_0(6) \hat{W}(6,4) + \alpha G_0(3) \hat{W}(3,4)$$

Random Walk Solution

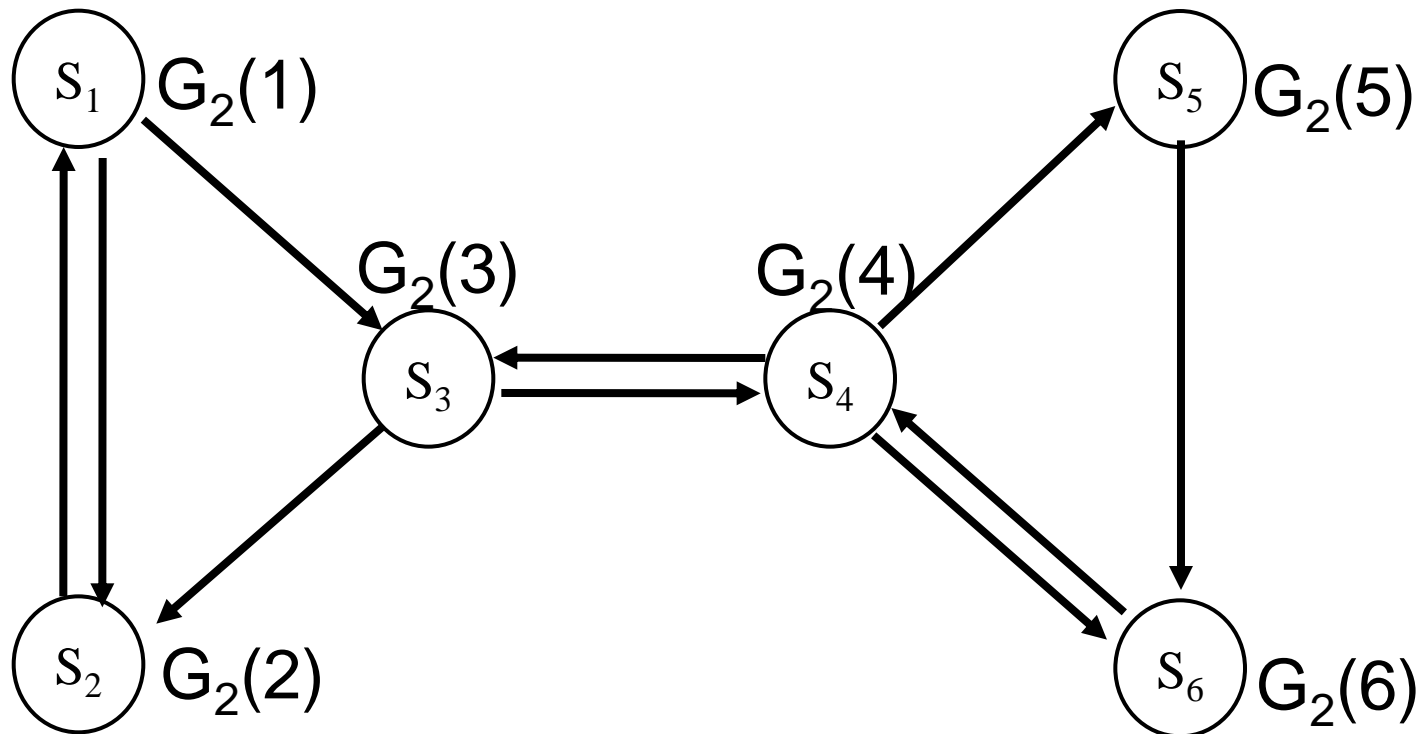
◆ Update the score for each sentence



$$G_2(4) = (1 - \alpha) I(S_4, d) + \alpha G_1(6) \hat{W}(6,4) + \alpha G_1(3) \hat{W}(3,4)$$

Random Walk Solution

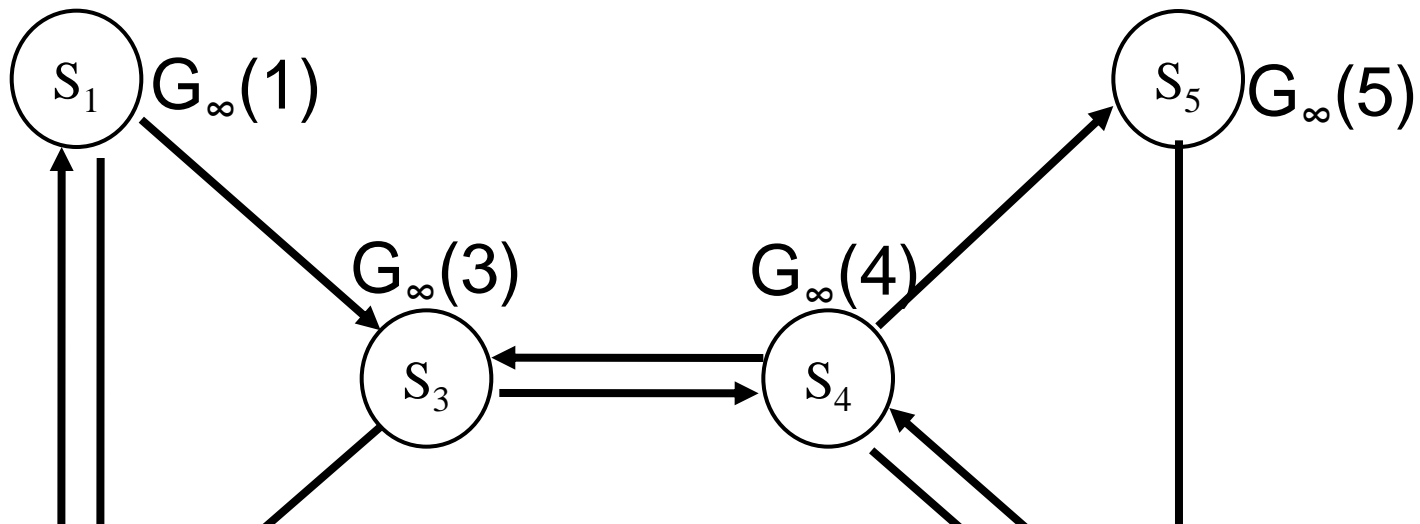
◆ *The process is repeated*



$$G_3(4) = (1 - \alpha)I(S_4, d) + \alpha G_2(6)\hat{W}(6,4) + \alpha G_2(3)\hat{W}(3,4)$$

Random Walk Solution

- ◆ *The process is repeated*



- ◆ *According to the theory of random walk:*
 - *The score of each node would finally converge.*
- ◆ *The converged score $G_\infty(i)$ is actually $G(i)$ satisfying*

$$G(i) = (1 - \alpha)I(S_i, d) + \alpha \sum_{S_j \in in(i)} G(j) \hat{W}(j, i)$$

Graph-based Summarization Approach

Find a set of new scores based on graph structure

$\{G(i)$ for each sentence S_i in document $d\}$ which satisfies

$$G(i) = (1 - \alpha)I(S_i, d) + \alpha \sum_{S_j \in in(i)} G(j) \hat{W}(j, i)$$

$$I(S, d) = \sum_{i=1}^n [s(t_i, d) \cdots] + \cdots$$

Importance score $i=1$ term statistical measure

$$I'(S_i, d) = I(S_i, d)^{1-\delta} G(i)^\delta$$

New scores: Consider graph structure

For summary selection

Original importance score based on terms in the sentences

Experimental Setup (1/2)

- Corpus: course offered in National Taiwan University
 - Mandarin Chinese embedded by English words
 - Single speaker
 - 45.2 hours
- ASR System
 - Bilingual AM with model adaptation [1]
 - LM with adaptation using random forests [2]

Language	Mandarin	English	Overall
Acc (%)	78.15	53.44	76.26

[1] Ching-Feng Yeh, et al., "Bilingual Acoustic Model Adaptation by Unit Merging on Different Levels and Cross-level Integration," Interspeech, 2011.

[2] Ching-Feng Yeh, et al., "An Integrated Framework for Transcribing Mandarin-English Code-mixed Lectures with Improved Acoustic and Language Modeling," ISCSLP, 2010.

Experimental Setup (2/2)

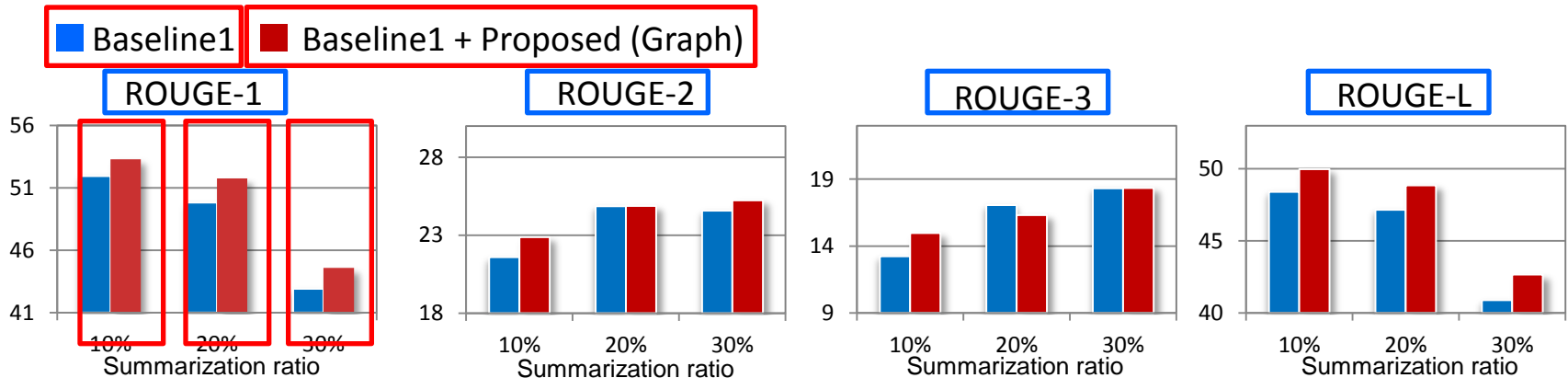
o Spoken Documents

- We segmented the whole lecture into 155 documents by topic segmentation
- 34 documents out of the 155 were tested.
- The average length of each document was about 17.5 minutes
- Human produced reference summaries for each document

o Evaluation

- o ROUGE-1, ROUGE-2, ROUGE-3
- o ROUGE-L: Longest Common Subsequence (LCS)

Experimental Results

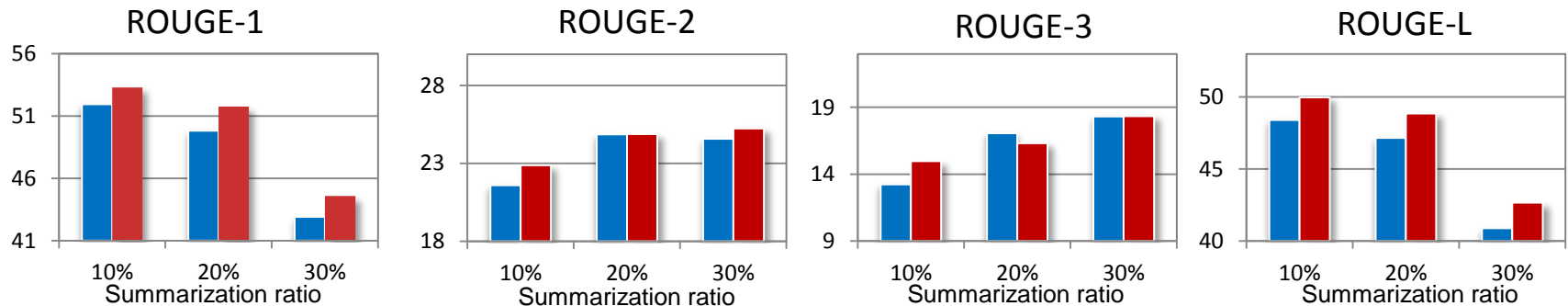


Baseline1: $I(S_i, d)$ – importance score using latent topic entropy term statistical measure

Baseline1+Proposed: $I(S_i, d)G(i)$

Experimental Results

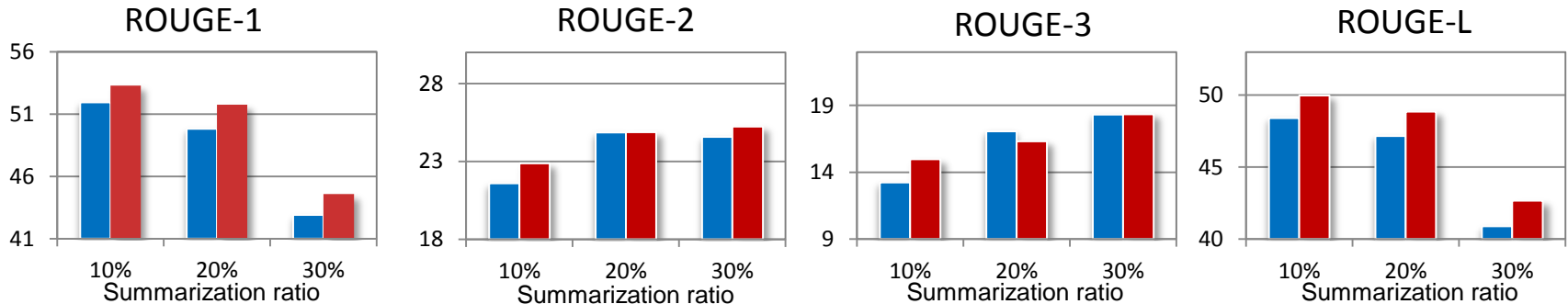
■ Baseline1 ■ Baseline1 + Proposed (Graph)



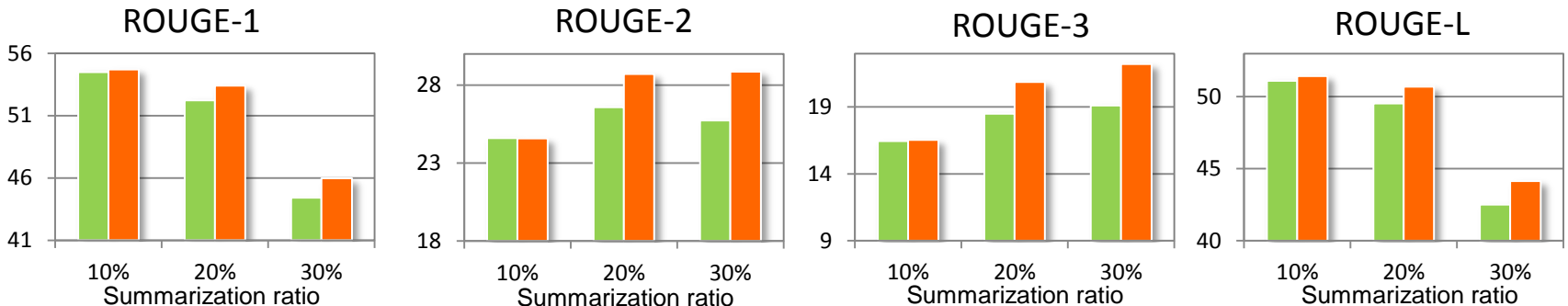
◆ The proposed approach outperformed the first baseline in most cases. (Compare blue and red bars)

Experimental Results

■ Baseline1 ■ Baseline1 + Proposed (Graph)



■ Baseline2 ■ Baseline2 + Proposed (Graph)

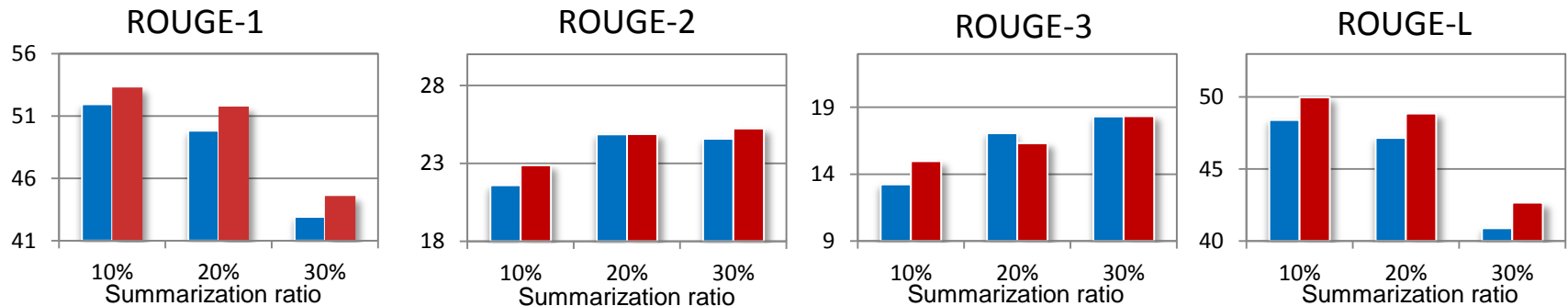


Baseline2: $I(S_i, d)$ – importance score using key-term based statistical measure

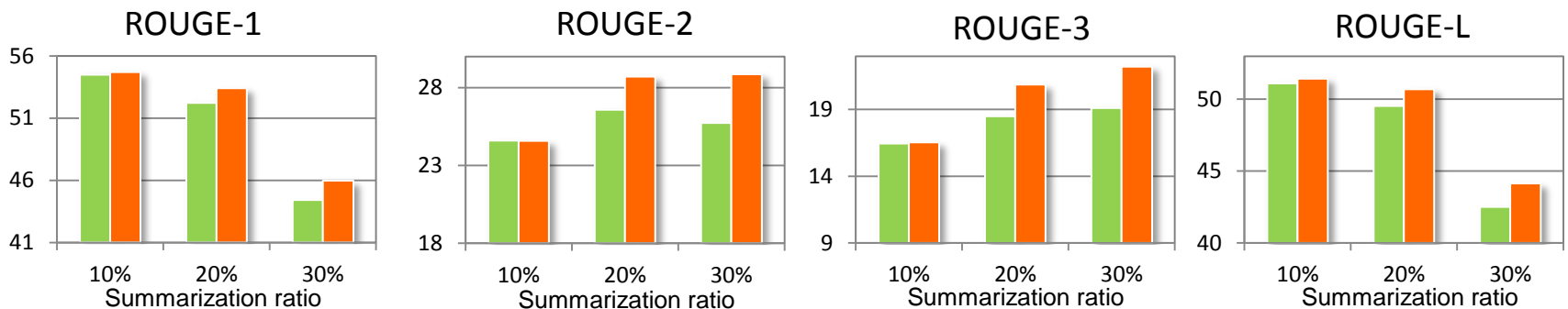
Baseline2+Proposed: $I(S_i, d)G(i)$

Experimental Results

■ Baseline1 ■ Baseline1 + Proposed (Graph)



■ Baseline2 ■ Baseline2 + Proposed (Graph)



◆ The proposed approach always outperformed the second baseline. (Compare green and orange bars)

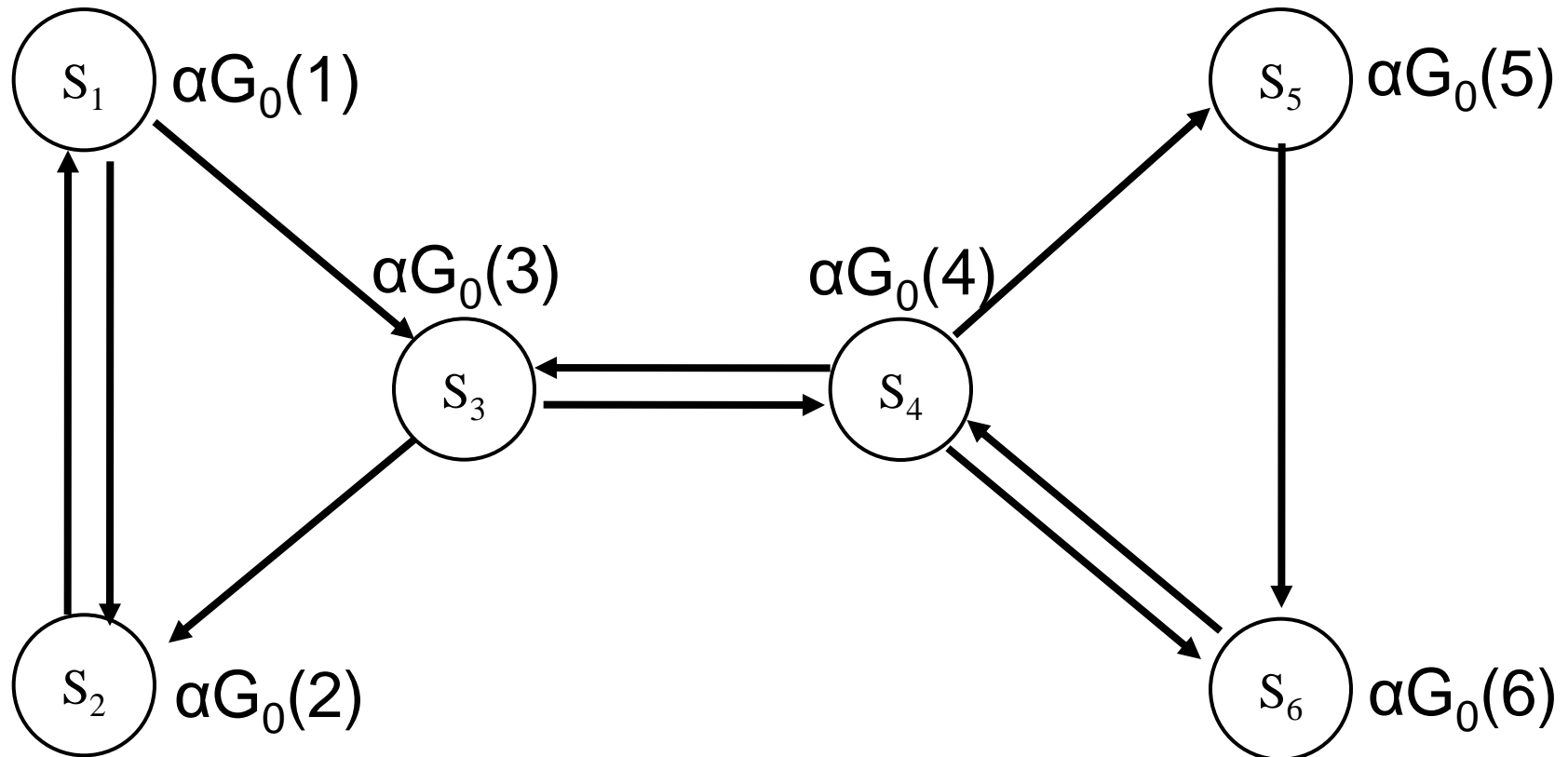
Conclusions

- The performance of summarization can be improved by
 - Graph-based approach considering topical similarity
 - This offers a way to globally consider all sentences in a document for summarization rather than considers each sentence individually

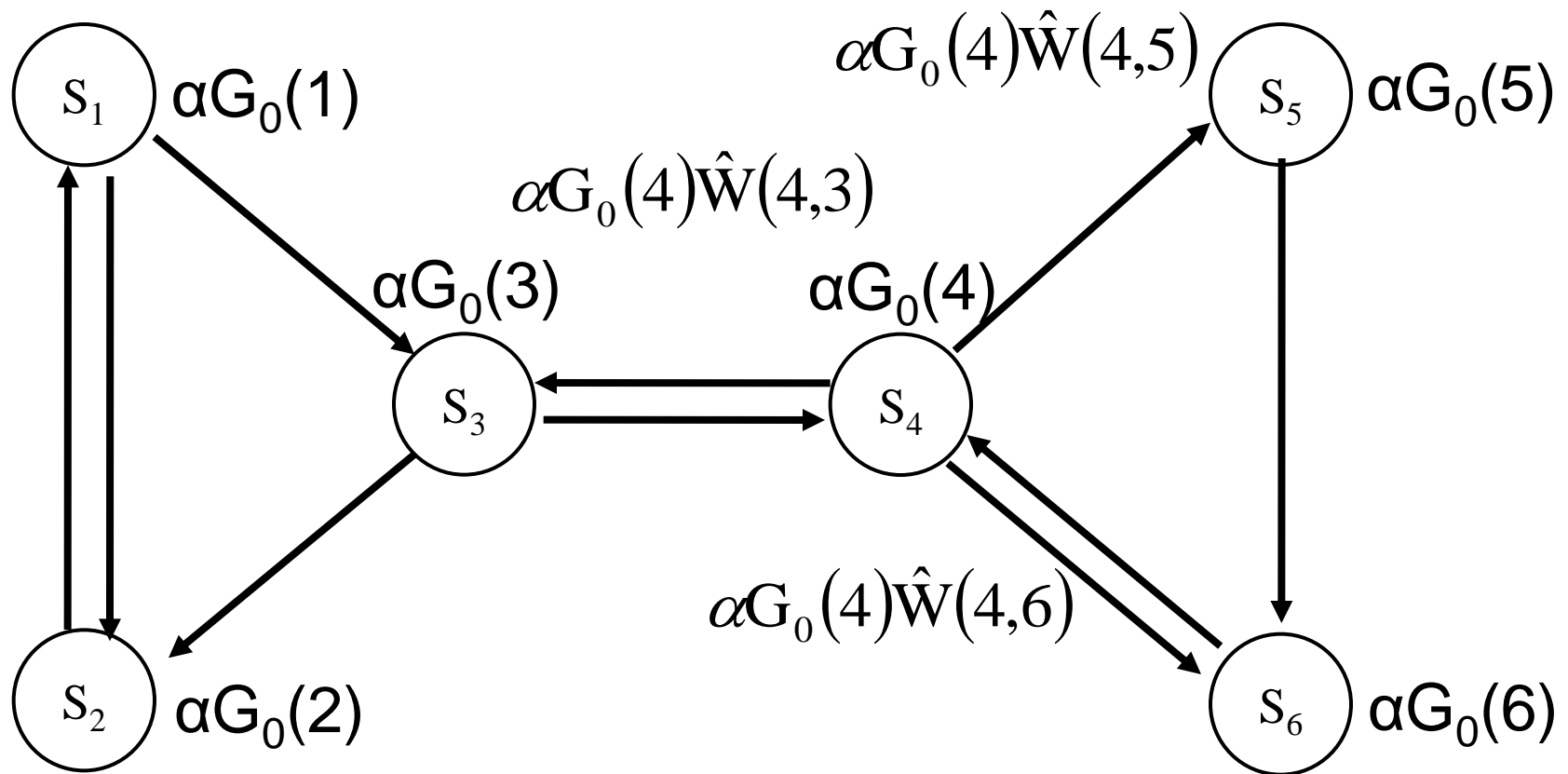


Thanks for your attention! 😊
Q & A

Random Walk Solution

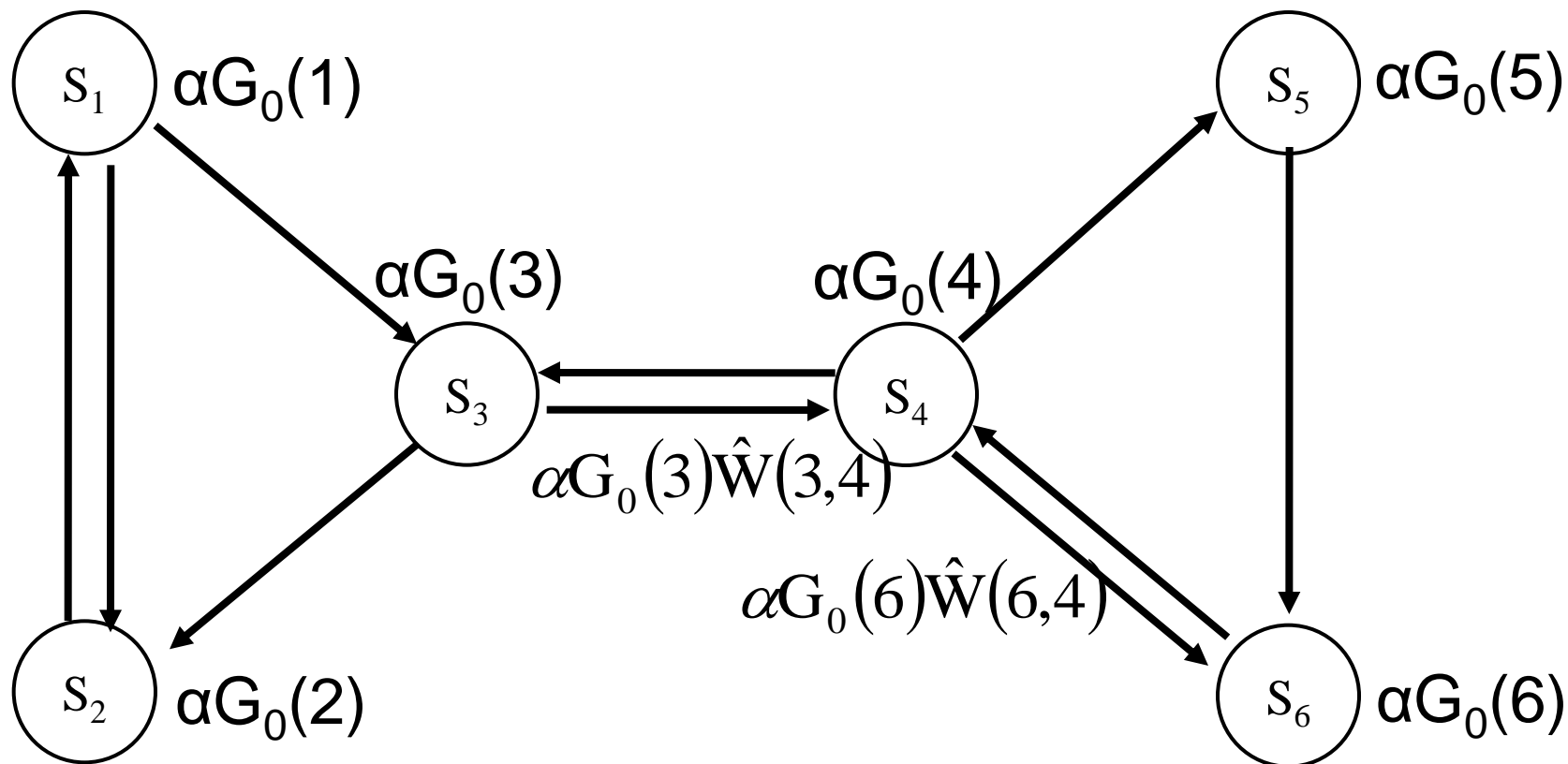


Random Walk Solution

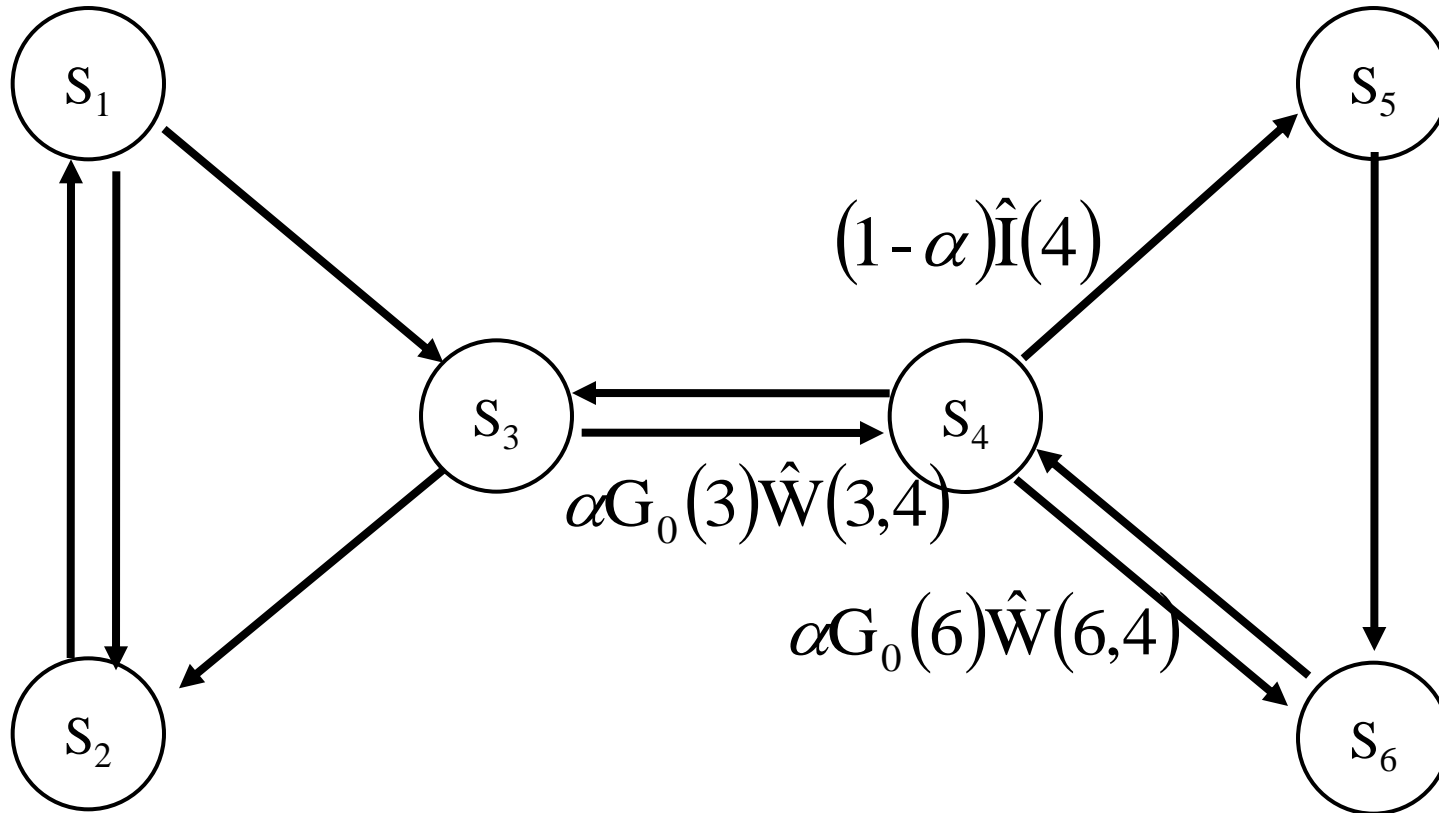


$$\hat{W}(j,i) = \frac{W(j,i)}{\sum_{S_k \in out(j)} W(j,k)}$$

Random Walk Solution



Random Walk Solution



$$G_1(4) = (1 - \alpha)\hat{I}(4) + \alpha G_0(3)\hat{W}(3,4) + \alpha G_0(6)\hat{W}(6,4)$$

Mathematical Formulation

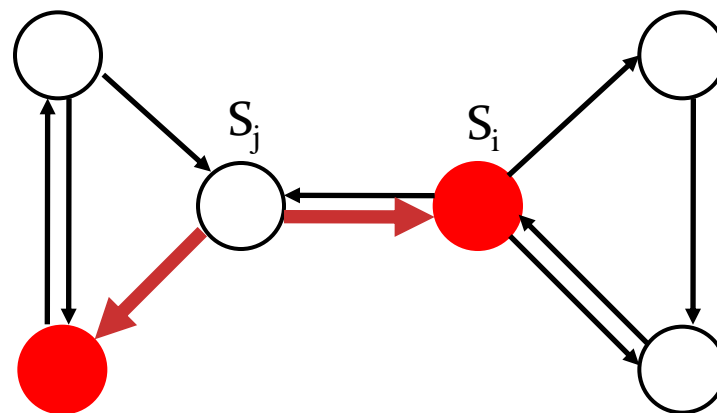
Find a set of new scores based on graph structure

$\{G(i)$ for each sentence S_i in document $d\}$ which satisfies

$$G(i) = (1 - \alpha)I(S_i, d) + \alpha \sum_{S_j \in in(i)} G(j) \hat{W}(j, i)$$

$$\hat{W}(j, i) = \frac{W(j, i)}{\sum_{S_k \in out(j)} W(j, k)}$$

$$\rightarrow \sum_{S_k \in out(j)} \hat{W}(j, k) = 1$$



Mathematical Formulation

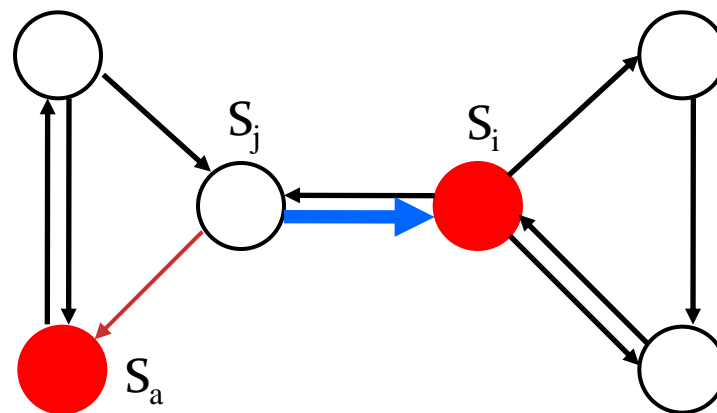
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$$G(i) = (1 - \alpha)I(S_i, d) + \alpha \sum_{S_j \in in(i)} G(j) \hat{W}(j, i)$$

The amount of score S_j propagate to S_i is

$$G(j) \frac{W(j, i)}{W(j, i) + W(j, a)}$$



Mathematical Formulation

Find a set of new scores based on graph structure

$\{G(i)$ for each sentence S_i in document $d\}$ which satisfies

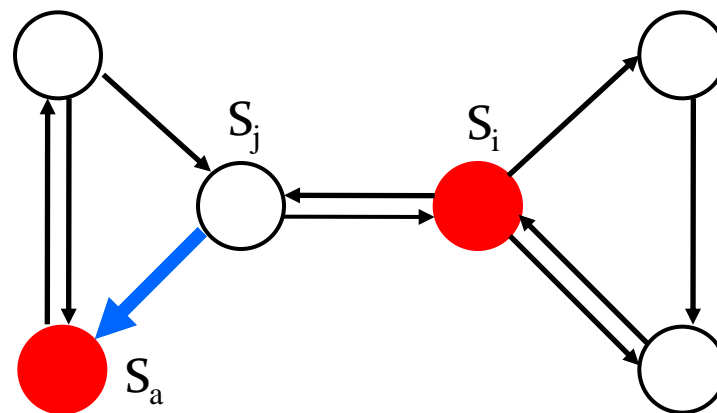
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The amount of score S_j propagate to S_i is

$$G(j) \frac{W(j, i)}{W(j, i) + W(j, a)}$$

The amount of score S_j propagate to S_a is

$$G(j) \frac{W(j, a)}{W(j, i) + W(j, a)}$$

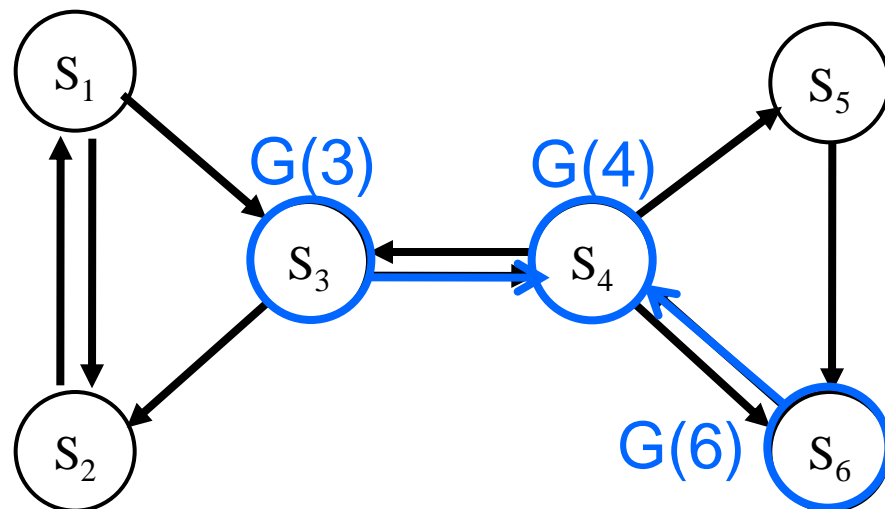


Mathematical Formulation – an Example

Find $G(1)$, $G(2)$, $G(3)$, $G(4)$, $G(5)$, $G(6)$ such that

$$\hat{W}(3,4) = \frac{W(3,4)}{W(3,2) + W(3,4)}$$

$$\hat{W}(6,4) = W(6,4)$$



$$G(4) = (1 - \alpha) I(S_4, d) + \alpha G(6) \hat{W}(6,4) + \alpha G(3) \hat{W}(3,4)$$

depends on S_4 itself

Depends on topically similar sentences (S_3 and S_6)