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

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Outline

Introduction

- Oraph-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
- Experiments
- Conclusion

Introduction –

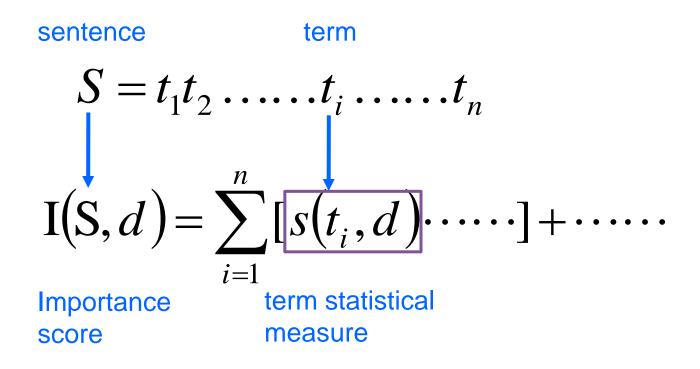
Extractive Summarization (1/2)

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

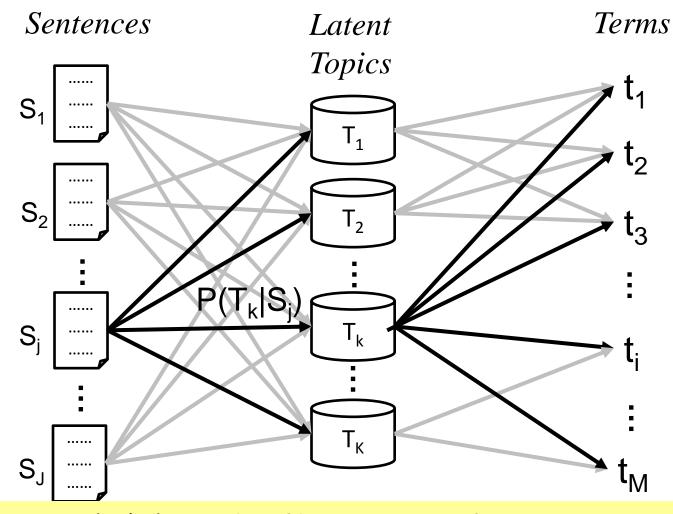
Introduction –

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)



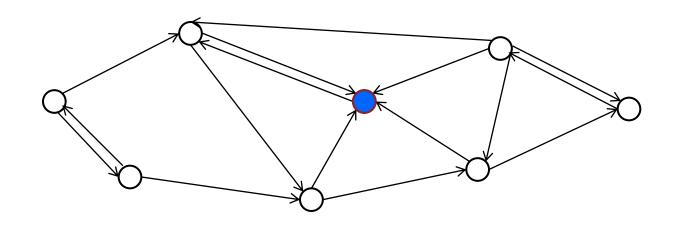
Introduction – PLSA



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

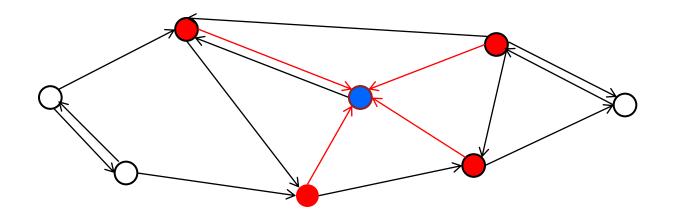
Proposed Approach (1/2)

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



Proposed Approach (1/2)

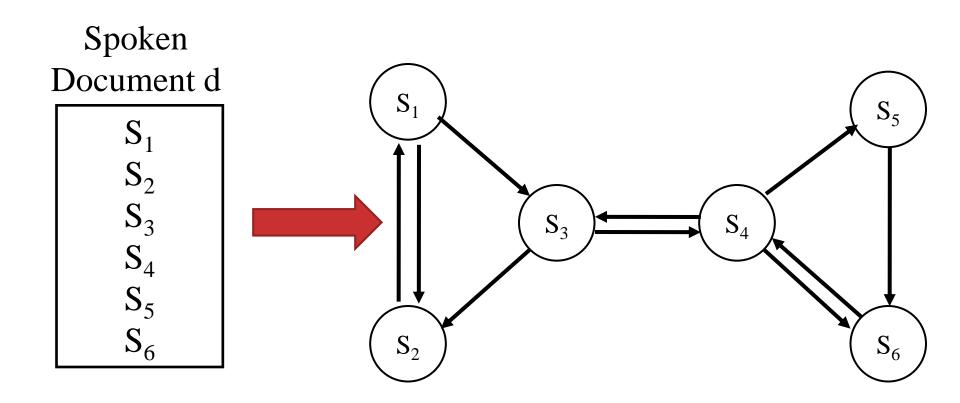
- Basic idea
 - Not only the sentences with high importance score based on statistical measure should be considered as indicative sentence
 - But the sentences topically similar to the indicative sentences should also be considered as indicative



Proposed Approach (2/2)

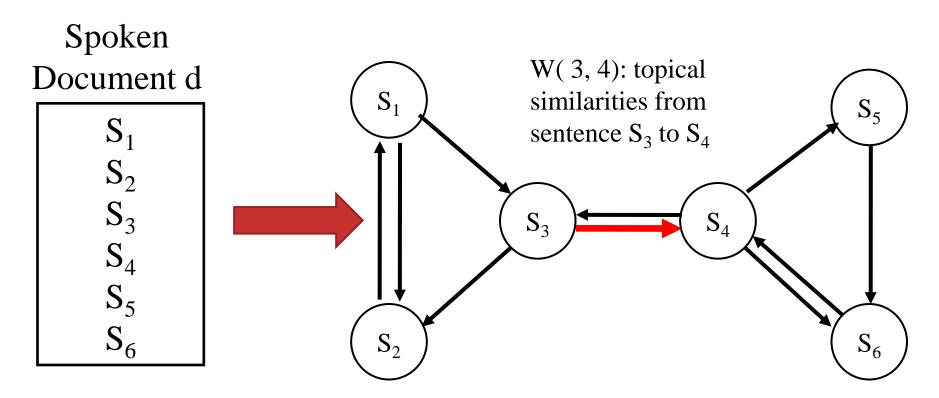
- Graph-based approach
 - Sentences in a spoken document are nodes on a graph, and topical similarities of sentences are weights of edges.
 - Use random walk to obtain new scores for summary selection
 - → all sentences in the document can be jointly considered rather than individually.

Graph Construction (1/2)



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

Graph Construction (1/2)



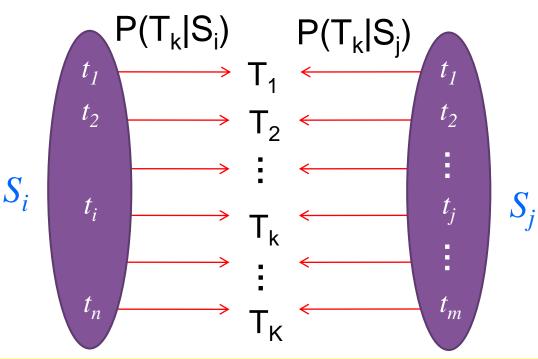
W(i, j) ($S_i \rightarrow S_j$): *Topical similarity* from sentence S_i to S_j (based on *PLSA latent topics* of sentences)

Graph Construction (2/2)

- Topical Similarities

\circ Topical Similarity from sentences S_i to S_j

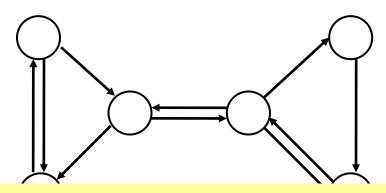
• Edge weight W(i, j) (sentence $S_i \rightarrow \text{sentence } S_j$)



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

Find a set of new scores based on graph structure $\{G(i) \text{ for each sentence } S_i \text{ in document } d\}$ which satisfies

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



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

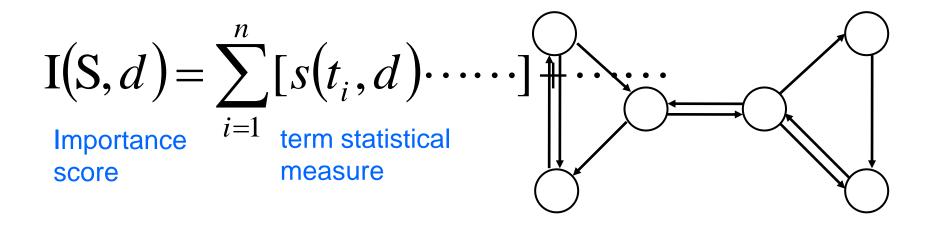
Find a set of new scores based on graph structure $\{G(i) \text{ for each sentence } S_i \text{ in document } d\}$ which satisfies

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

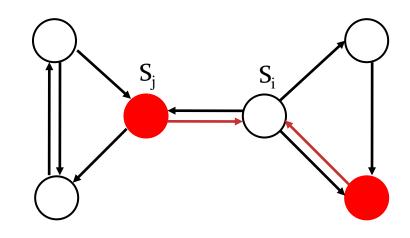
The original importance score of node S_i (weighted by 1- α)

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

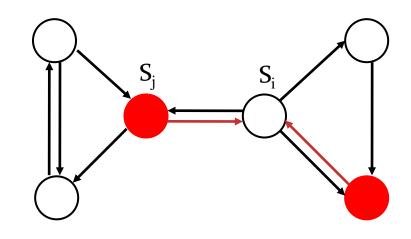
$$\mathbf{G}(i) = (1 - \alpha)\mathbf{I}(\mathbf{S}_i, d) + \alpha \sum_{S_j \in in(i)} \mathbf{G}(j)\mathbf{\hat{W}}(j, i)$$



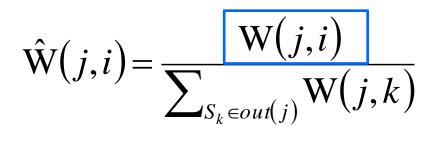
$$\mathbf{G}(i) = (1 - \alpha)\mathbf{I}(\mathbf{S}_i, d) + \alpha \sum_{\substack{S_j \in in(i)}} \mathbf{G}(j)\hat{\mathbf{W}}(j, i)$$

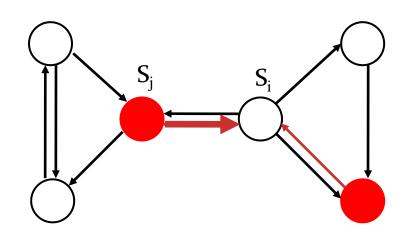


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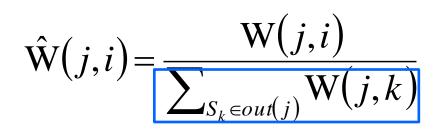
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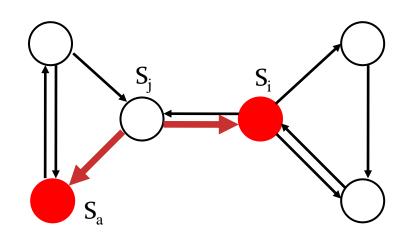


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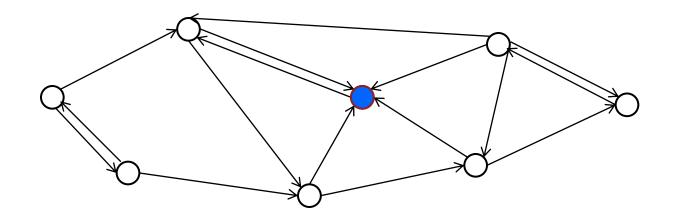
$$\mathbf{G}(i) = (1 - \alpha)\mathbf{I}(\mathbf{S}_i, d) + \alpha \sum_{S_j \in in(i)} \mathbf{G}(j) \hat{\mathbf{W}}(j, i)$$



The scores propagate from a node to all other nodes <u>sums to unity</u>.



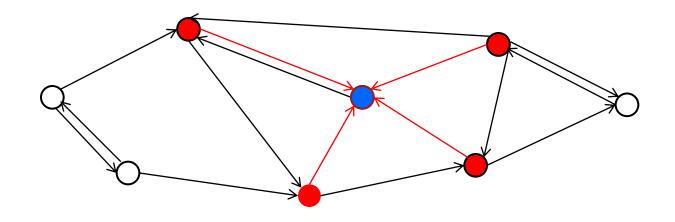
Mathematical Formulation $G(i) = (1 - \alpha)I(S_i, d) + \alpha \sum_{S_j \in in(i)} G(j)\hat{W}(j, i)$



G(i) can obtain higher score when

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

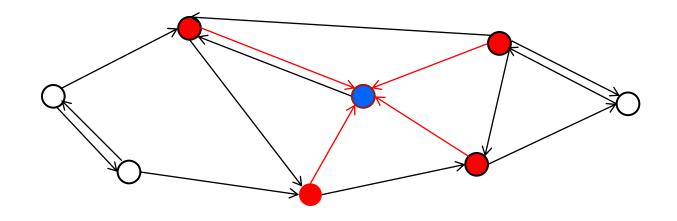
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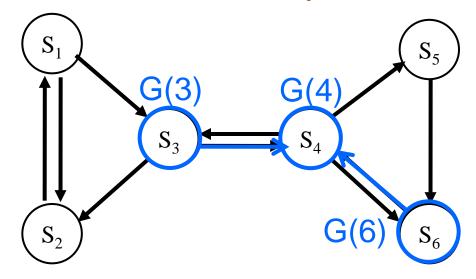
Mathematical Formulation $G(i) = (1 - \alpha)I(S_i, d) + \alpha \sum_{S_j \in in(i)} G(j)\hat{W}(j, i)$



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



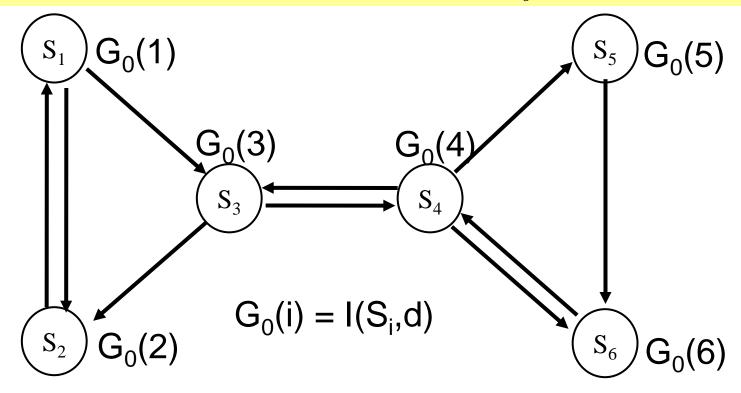
 $G(4) = (1 - \alpha)I(S_4, d) + \alpha G(6)\hat{W}(6, 4) + \alpha G(3)\hat{W}(3, 4)$

Mathematical Formulation –
Equations to be solved
Find G(1), G(2), G(3), G(4),
G(5), G(6) such that

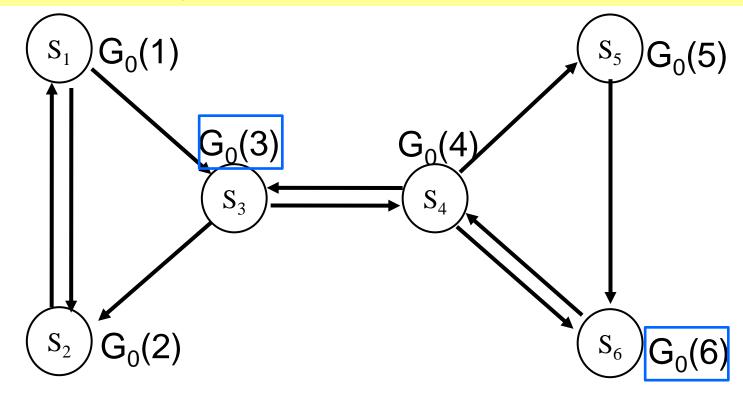
$$G(1) = (1 - \alpha)I(S_1, d) + \alpha G(2)\hat{W}(2, 1)$$

 $G(2) = (1 - \alpha)I(S_2, d) + \alpha G(3)\hat{W}(3, 2)$
 $G(3) = (1 - \alpha)I(S_3, d) + \alpha G(1)\hat{W}(1, 3) + \alpha G(4)\hat{W}(4, 3)$
 $G(4) = (1 - \alpha)I(S_4, d) + \alpha G(6)\hat{W}(6, 4) + \alpha G(3)\hat{W}(3, 4)$
 $G(5) = (1 - \alpha)I(S_5, d) + \alpha G(4)\hat{W}(4, 5)$
 $G(6) = (1 - \alpha)I(S_5, d) + \alpha G(4)\hat{W}(4, 5) + \alpha G(5)\hat{W}(5, 6)$
How to solve these equations to obtain $G(1)$, $G(2)$, $G(6)$?
Solve the problem iteratively (random walk)

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

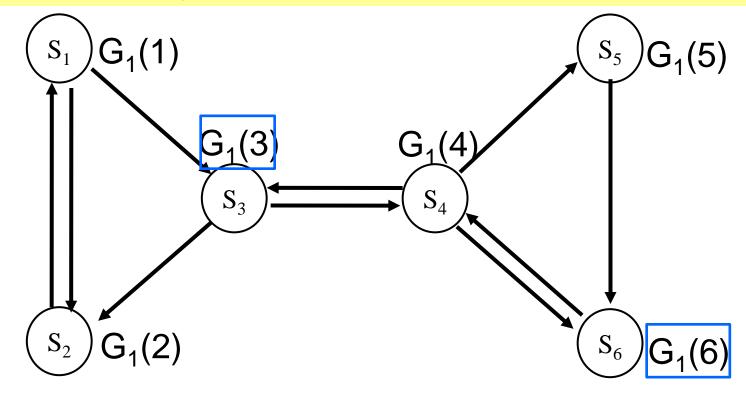


Update the score for each sentence



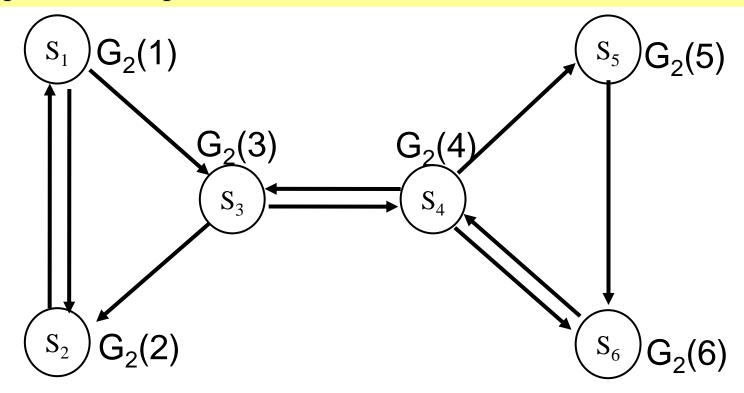
 $G_{1}(4) = (1 - \alpha) I(S_{4}, d) + \alpha G_{0}(6) \hat{W}(6, 4) + \alpha G_{0}(3) \hat{W}(3, 4)$

Update the score for each sentence



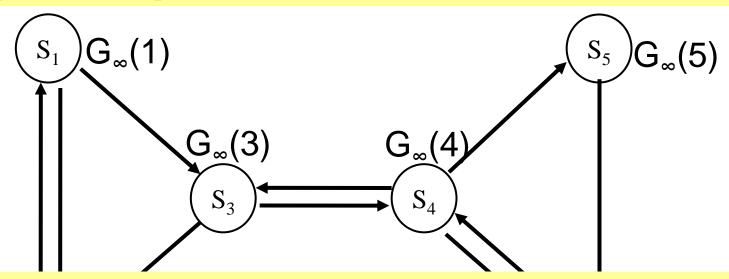
 $G_{2}(4) = (1 - \alpha)I(S_{4}, d) + \alpha G_{1}(6)\hat{W}(6, 4) + \alpha G_{1}(3)\hat{W}(3, 4)$

The process is repeated



 $G_{3}(4) = (1 - \alpha)I(S_{4}, d) + \alpha G_{2}(6)\hat{W}(6, 4) + \alpha G_{2}(3)\hat{W}(3, 4)$

The process is repeated



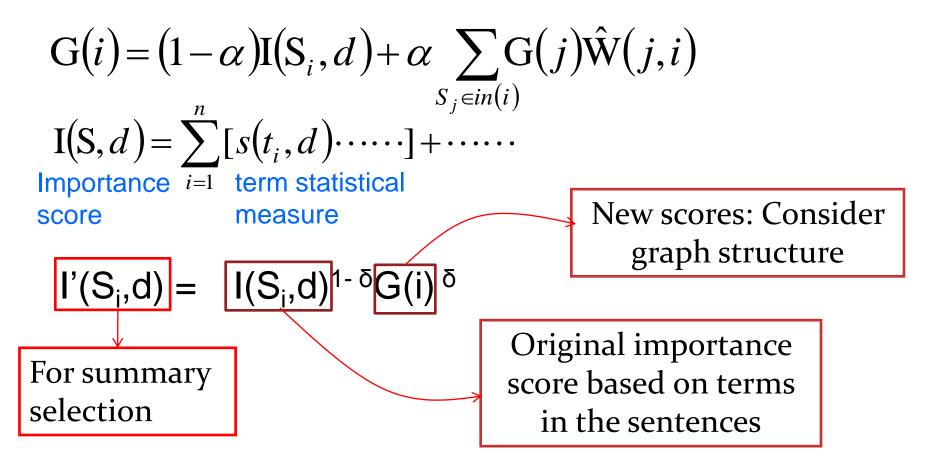
According to the theory of random walk:

The score of each node would finally converge.

The converged score $G_{\infty}(i)$ is actually G(i) satisfying

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

Graph-based Summarization Approach



Experimental Setup (1/2)

- Corpus: course offered in National Taiwan University
 - Mandarin Chinese embedded by English words
 - Single speaker
 - 0 45.2 hours
- ASR System
 - Bilingual AM with model adaptation [1]
 - IM with adaptation using random forests [2]

Language	Mandarin	English	Overall
Acc (%)	78.15	53.44	76.26

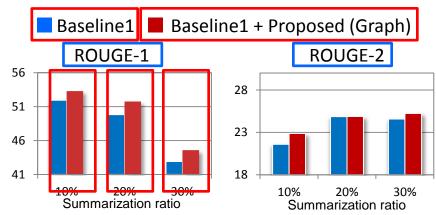
[1] Ching-Feng Yeh, et al., "Bilingual Acoustic Model Adaptation by Unit Merging on Different Levels and Cross-level Integration, "Interspeech, 2011.

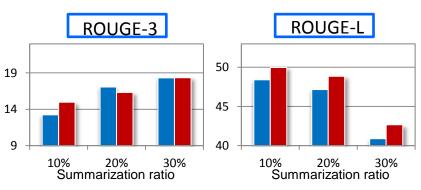
[2] Ching-Feng Yeh, et al., "An Integrated Framework for Transcribing Mandarin-English Code-mixed Lectures with Improved Acoustic and Language Modeling," ISCSLP, 2010.

Experimental Setup (2/2)

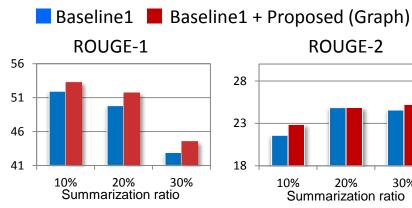
Spoken Documents

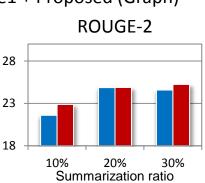
- We segmented the whole lecture into 155 documents by topic segmentation
- 34 documents out of the 155 were tested.
- The average length of each document was about 17.5 minutes
- Human produced reference summaries for each document
- Evaluation
 - ROUGE-1, ROUGE-2, ROUGE-3
 - ROUGE-L: Longest Common Subsequence (LCS)

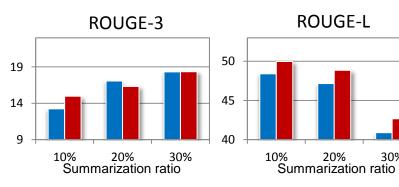




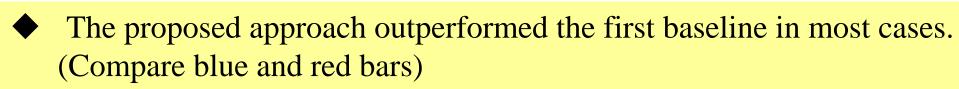
Baseline1: $I(S_i,d)$ – importance score using latent topic entropy term statistical measure Baseline1+Proposed: $I(S_i,d)G(i)$

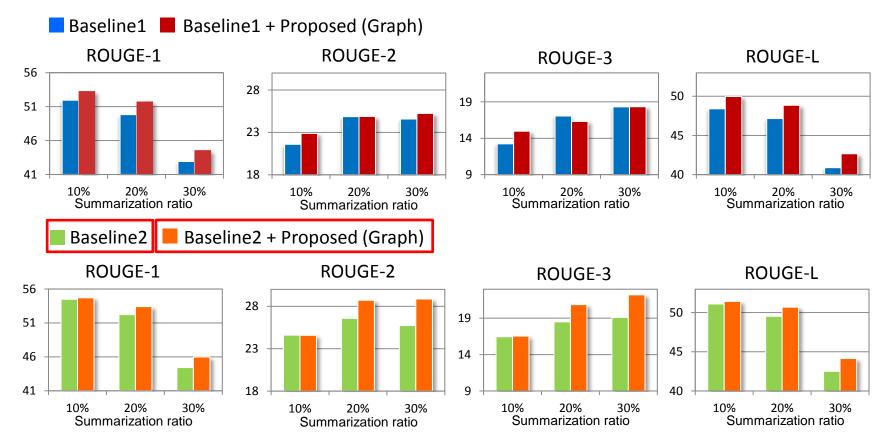






30%

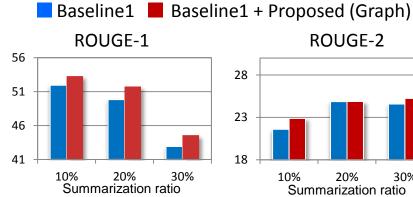


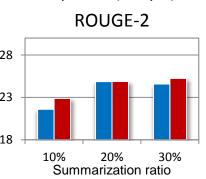


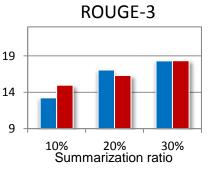
Baseline2: I(S_i,d) – importance score using key-term based statistical measure

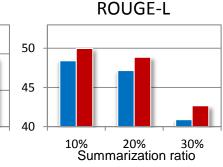
Baseline2+Proposed: I(S_i,d)G(i)

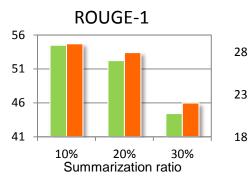
Baseline2 Baseline2 + Proposed (Graph)

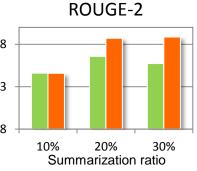


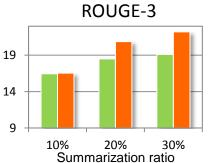




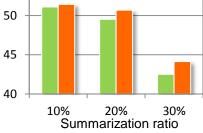












The proposed approach always outperformed the second baseline. (Compare green and orange bars)

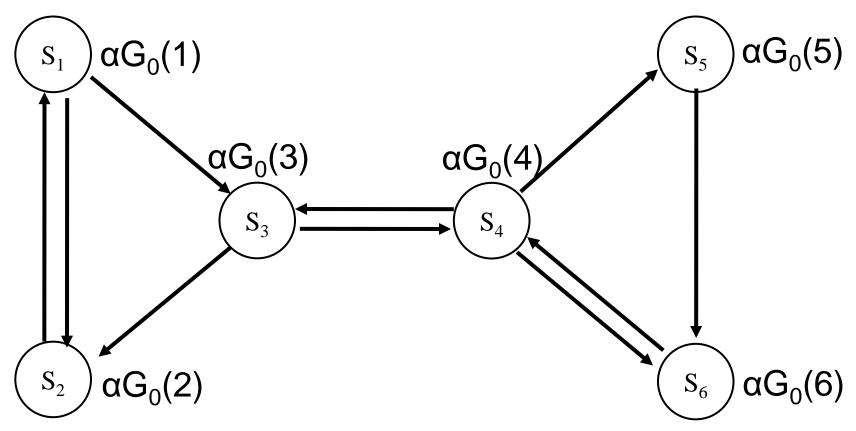
Conclusions

- 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

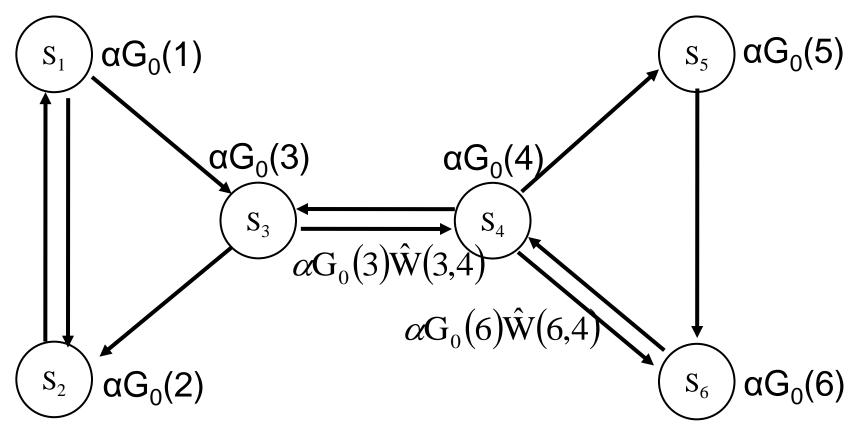


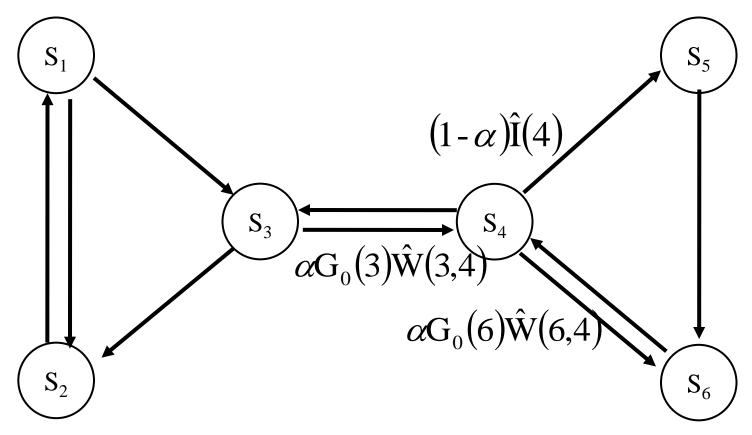
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Thanks for your attention! © Q&A



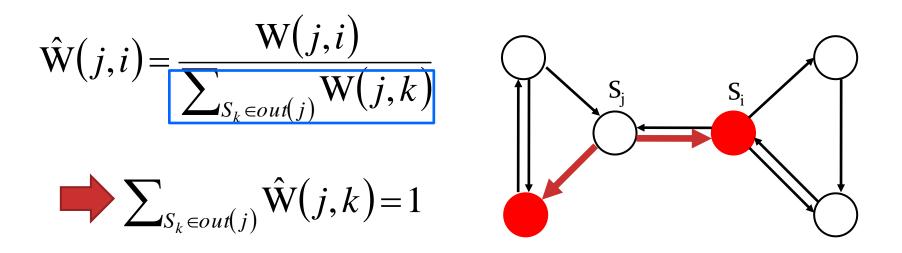
Random Walk Solution $\alpha G_0(4)\hat{W}(4,5)$ $\alpha G_0(1)$ $\alpha G_0(5)$ S_5 \mathbf{S}_1 $\alpha G_0(4)\hat{W}(4,3)$ $\alpha G_0(4)$ $\alpha G_0(3)$ **S**₃ S_4 $\alpha G_0(4) \hat{W}(4,6)$ S_2 $\alpha G_0(2)$ S_6 $\alpha G_0(6)$ $\hat{W}(j,i) = \frac{W(j,i)}{\sum_{S_k \in out(j)} W(j,k)}$





 $G_{1}(4) = (1 - \alpha)\hat{I}(4) + \alpha G_{0}(3)\hat{W}(3,4) + \alpha G_{0}(6)\hat{W}(6,4)$

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

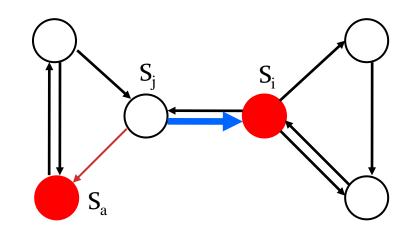


Find a set of new scores based on graph structure $\{G(i) \text{ for each sentence } S_i \text{ in document } d\}$ which satisfies

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

The amount of score S_j propagate to S_i is

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



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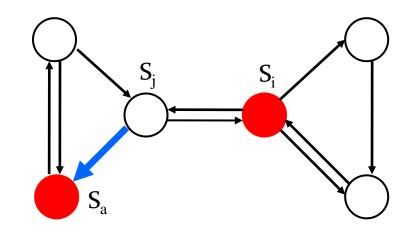
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The amount of score S_j propagate to S_i is

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

The amount of score S_j propagate to S_a is

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



Mathematical Formulation – an Example

