Intra-Speaker Topic Modeling for Improved Multi-Party Meeting Summarization with Integrated Random Walk

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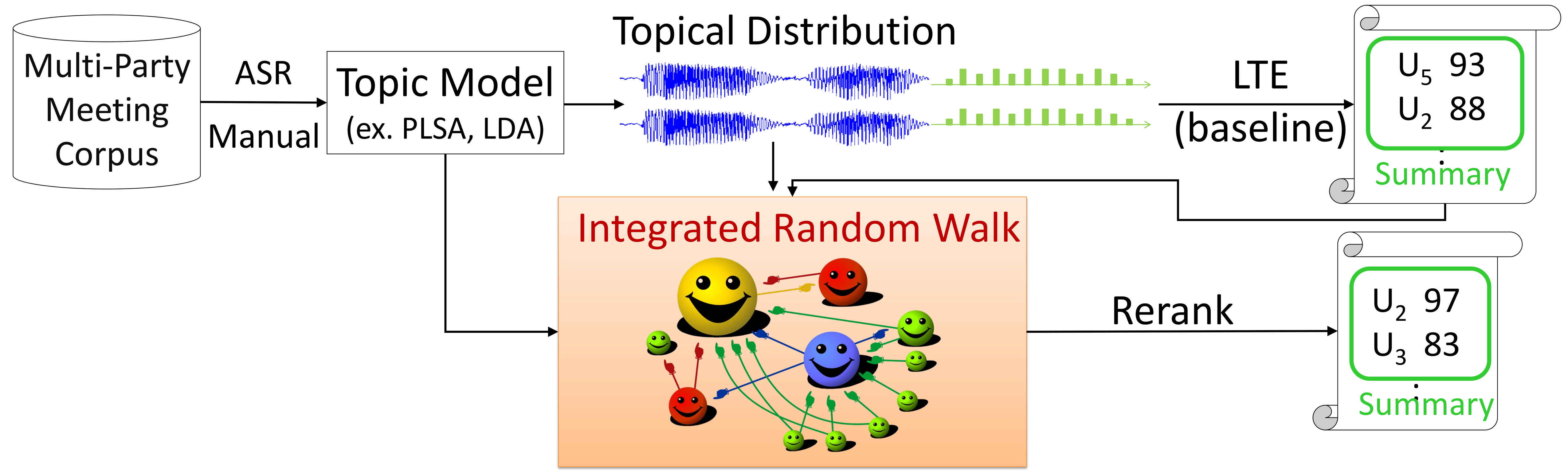
Summary

- **Idea:**
  - **Important utterances are topically/lexically similar to each other**
  - **Utterances from the same speaker usually focus on similar topics**
- **Approach for extractive summary**
  - **Construct a graph to represent the utterances in the document (node: utterance, edge: weighted by topical/lexical similarity)**
  - **Use the graph to compute importance of each utterance**



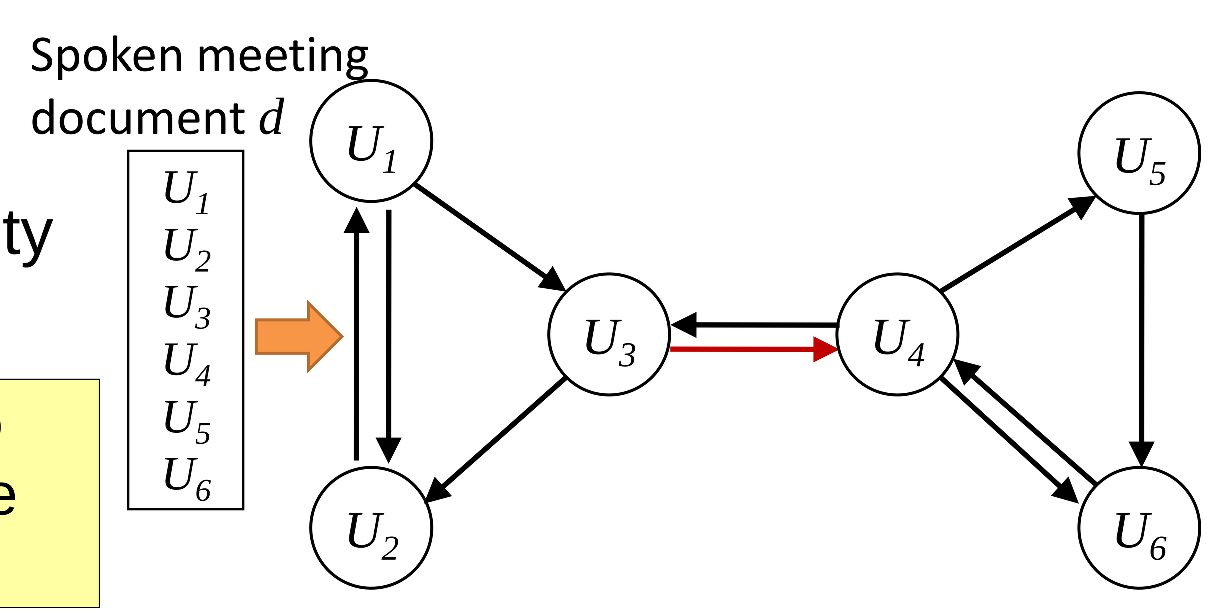
Graph Construction

- Graph Construction
  - Node: utterances in a doc.
  - Edge weight: topical/lexical similarity between utterances

> The utterances topically/lexically similar to more important utterances should be more important

- Intra-Speaker Topic Sharing
  - Weight the edge similarity if two utterances are from the same speaker

> The utterances from the same speaker can partially share the importance



① Topical edges: latent topic generative significance of utterance U_i to U_j based on PLSA (see paper)

② Lexical edges: TFIDF cos similarity

Integrated Random Walk

- **Basic Idea: high importance means**
  - **① Utterances with higher Latent Topic Entropy (original score)**
  - **② Utterances topically/lexically similar to the indicative utterances**
- Compute a set of new scores based on graph structure, S(Ui) satisfying

$$S(U_i) = (1-\alpha-\beta)\boxed{\hat{I}(U_i)} + \alpha \sum_{U_j \in in_t(U_i)} \boxed{\hat{\text{TopicSim}}(U_j, U_i) S(U_j)} + \beta \sum_{U_j \in in_l(U_i)} \boxed{\hat{\text{LexSim}}(U_j, U_i) S(U_j)}$$

Latent Topic Entropy (original importance score)

scores propagated from its neighbor weighted by topical similarity

scores propagated from its neighbor weighted by lexical similarity

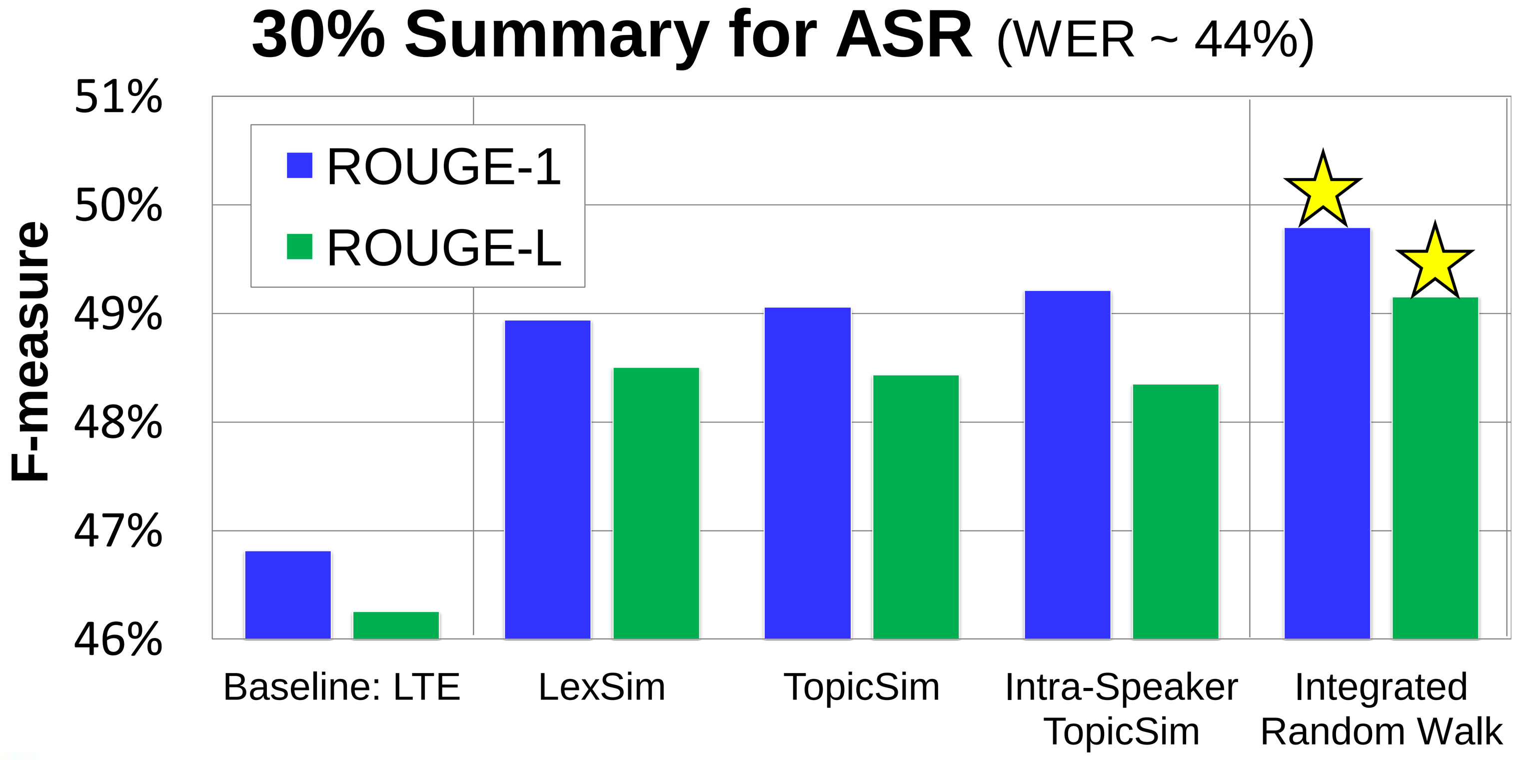
- Updated importance $\mathbf{v} = (1-\alpha-\beta)\mathbf{r} + \alpha \mathbf{P_t v} + \beta \mathbf{P_l v}$
  - → eigenvector of P' $= \left((1-\alpha-\beta)\mathbf{r}\mathbf{e}^{\mathbf{T}} + \alpha \mathbf{P_t} + \beta \mathbf{P_l}\right)\mathbf{v} = \mathbf{P}'\mathbf{v}$

Chen, Y.-N. et al. "Spoken lecture summarization by random walk over a graph constructed with automatically extracted key terms," in InterSpeech, 2011.
Erkan, G. and Radev, D. R. "LexRank: Graphbased lexical centrality as salience in text summarization" in Journal of Artificial Intelligence Research, 2004.

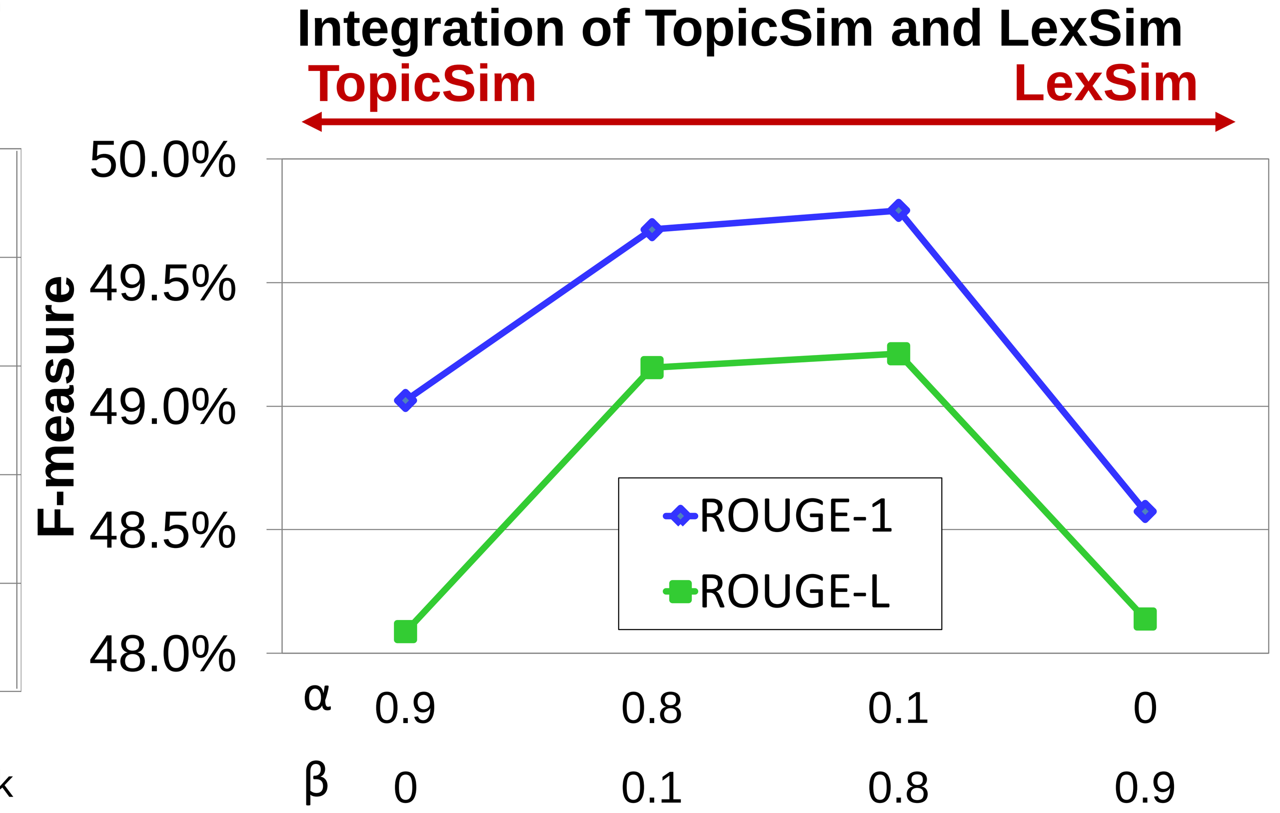
Experiments

- Dataset: 10 meetings from CMU Speech Group

30% Summary for ASR (WER ~ 44%)



Integration of TopicSim and LexSim



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Conclusions

- Graph-based approach can improve summarization performance using lexical or topical similarity
- Topics from the same speaker can be shared in the graph
- For manual transcriptions, random walk with intra-speaker topical similarity performs best
- For ASR transcriptions, integrated random walk performs best because lexical and topical similarity are additive
  - Lexical similarity measures word overlap
  - Topical similarity compensates the negative effects of recognition errors on similarity evaluated on word overlap to some extent