☺ Best Student Paper Nomination ☺

Integrating Intra-Speaker Topic Modeling and Temporal-Based Inter-Speaker Topic Modeling in Random Walk for Improved Multi-Party Meeting Summarization

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lti

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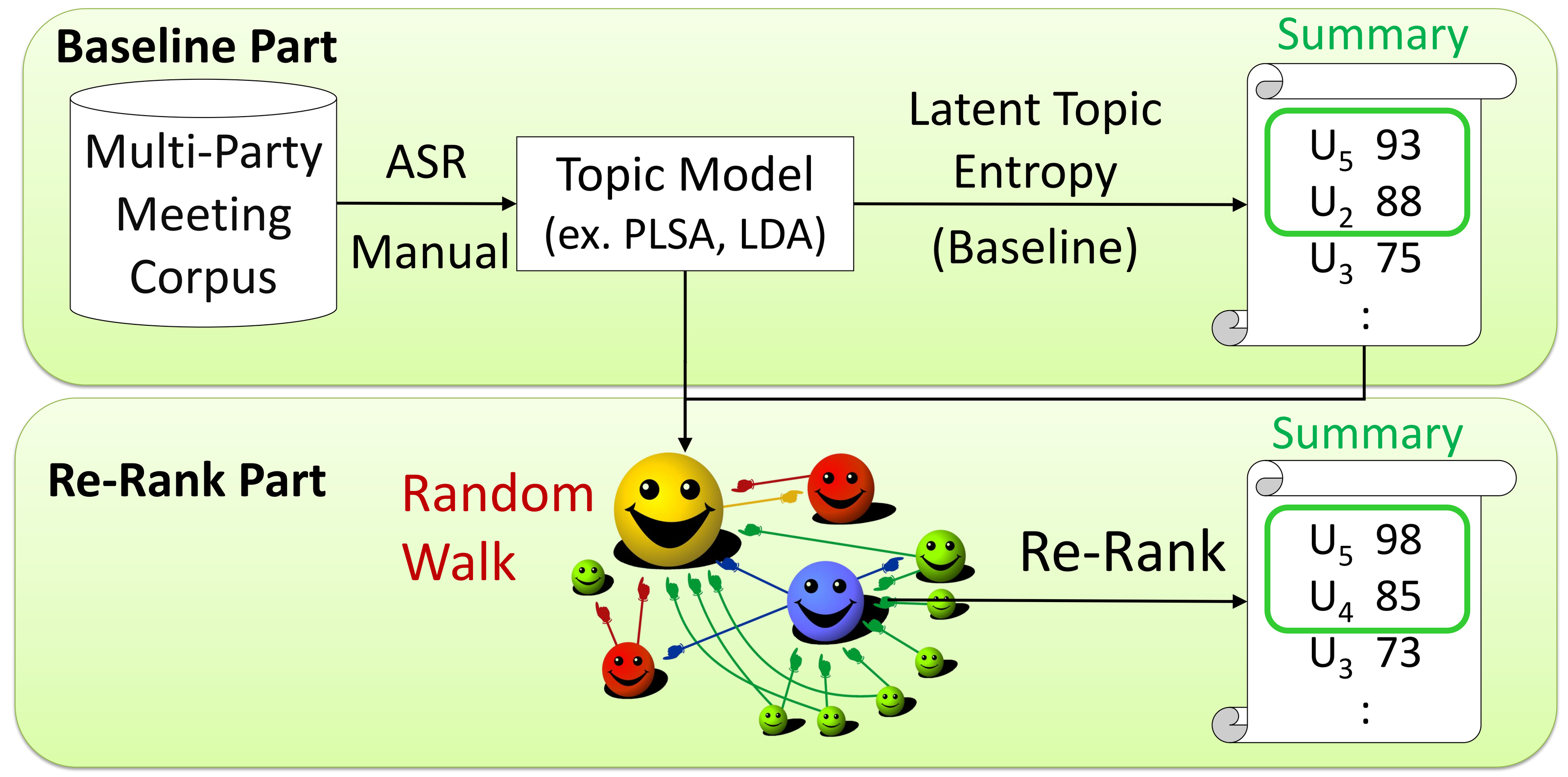
1. Summary

- **Idea:**
  - **Important utterances are topically similar to each other**
  - **Utterances from the same speaker usually focus on similar topics**
  - **Temporally adjacent utterances have similar topic distribution**
- **Approach for extractive summary**
  - **Construct a graph to represent the utterances in the doc. (node: utterance, edge: weighted by topical similarity)**
  - **Topic similarity models intra- and inter-speaker information**
  - **Use the graph to compute importance of each utterance**

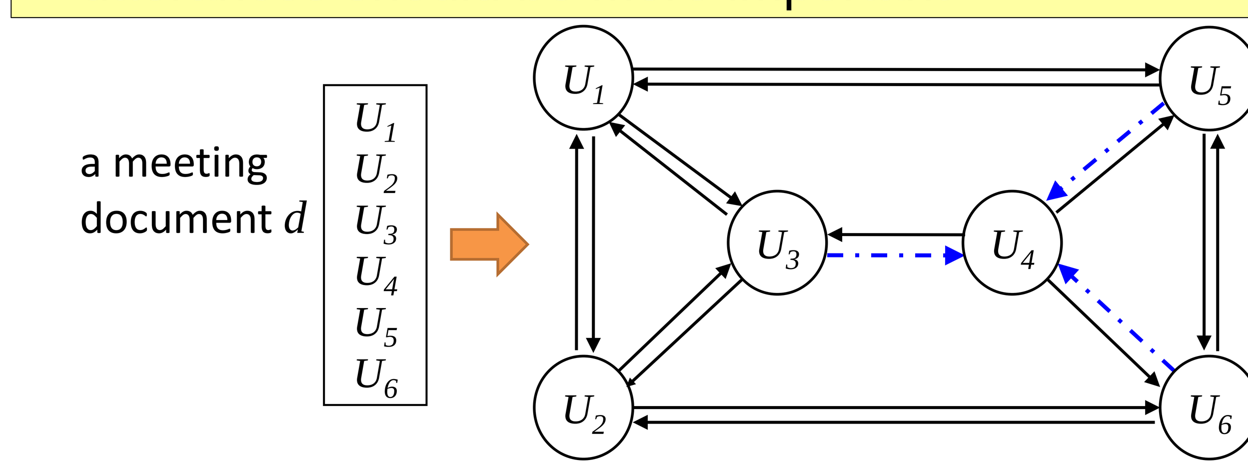


Flowchart of proposed approach

2. Graph Construction

- Graph Construction
  - Node: utterances in a document
  - Edge weight: topical similarity between utt.

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



Sim(U_i, U_j): latent topic generative significance of utterance U_i to U_j based on PLSA (see paper)

3. Intra/Inter-Speaker Topic Modeling

$$\mathrm{Sim}'(U_i,U_j)=\mathrm{Sim}(U_i,U_j)^{1+\boxed{w_{\text{intra}}(U_i,U_j)}+\boxed{w_{\text{inter}}(U_i,U_j)}}$$

Intra-Speaker Topic Modeling

Increase the edge similarity if two utterances are from the same speaker S_k

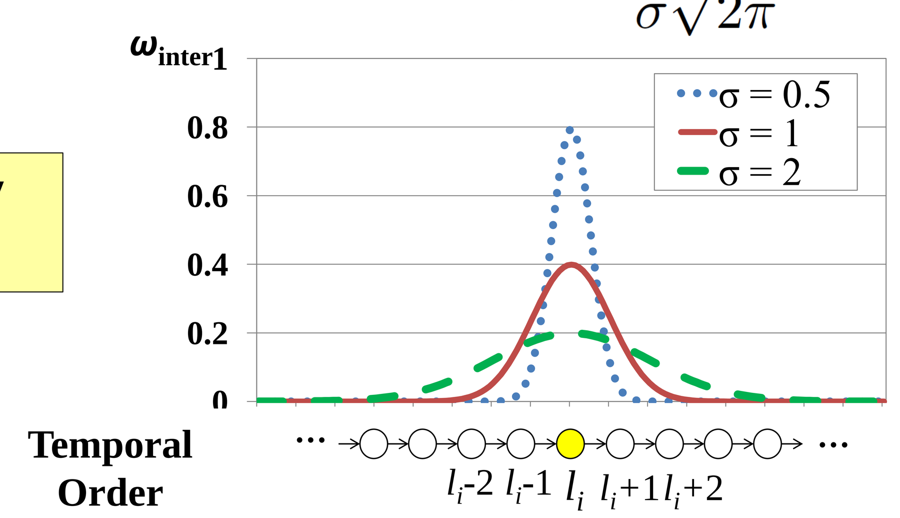
$$w_{\text{intra}}(U_i,U_j)=\begin{cases}+\delta & \text{, if } U_i\in S_k \text{ and } U_j\in S_k\\ -\delta & \text{, otherwise}\end{cases}$$

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

Inter-Speaker Topic Modeling

Increase the edge similarity if two utterances have a closer position in the dialogue based on normal distribution

$$w_{\text{inter}}(U_i,U_j)=\frac{1}{\sigma\sqrt{2\pi}}\exp\left(-\frac{(l_j-l_i)^2}{2\sigma^2}\right)$$



> Temporally adjacent utterances can partially share the importance

4. Random Walk

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

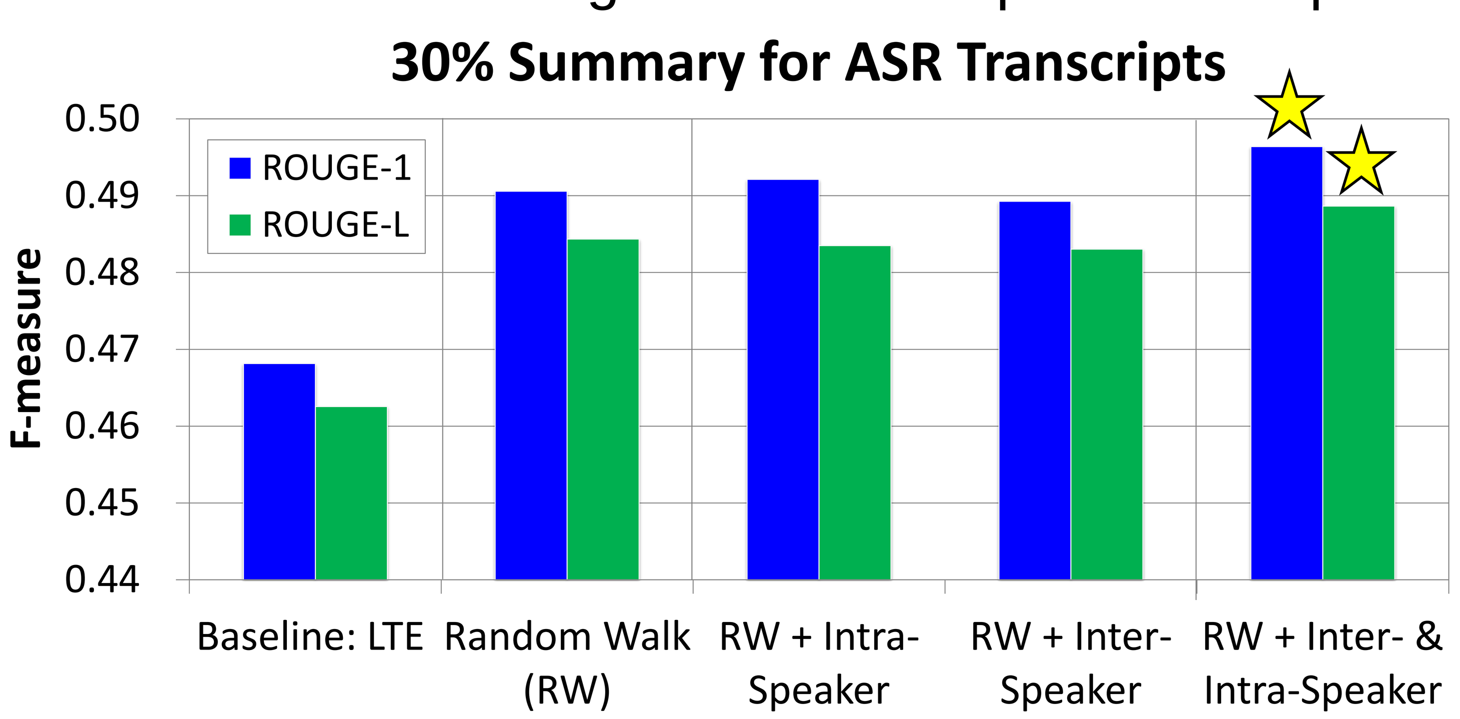
$$S(U_i)=(1-\alpha)\underbrace{\boxed{\hat{I}(U_i)}}_{\text{Latent Topic Entropy (original importance score)}}+\alpha\underbrace{\boxed{\sum_{U_j\in in(U_i)}\hat{\mathrm{Sim}}(U_j,U_i)S(U_j)}}_{\text{scores propagated from its neighbor weighted by topical similarity}}$$

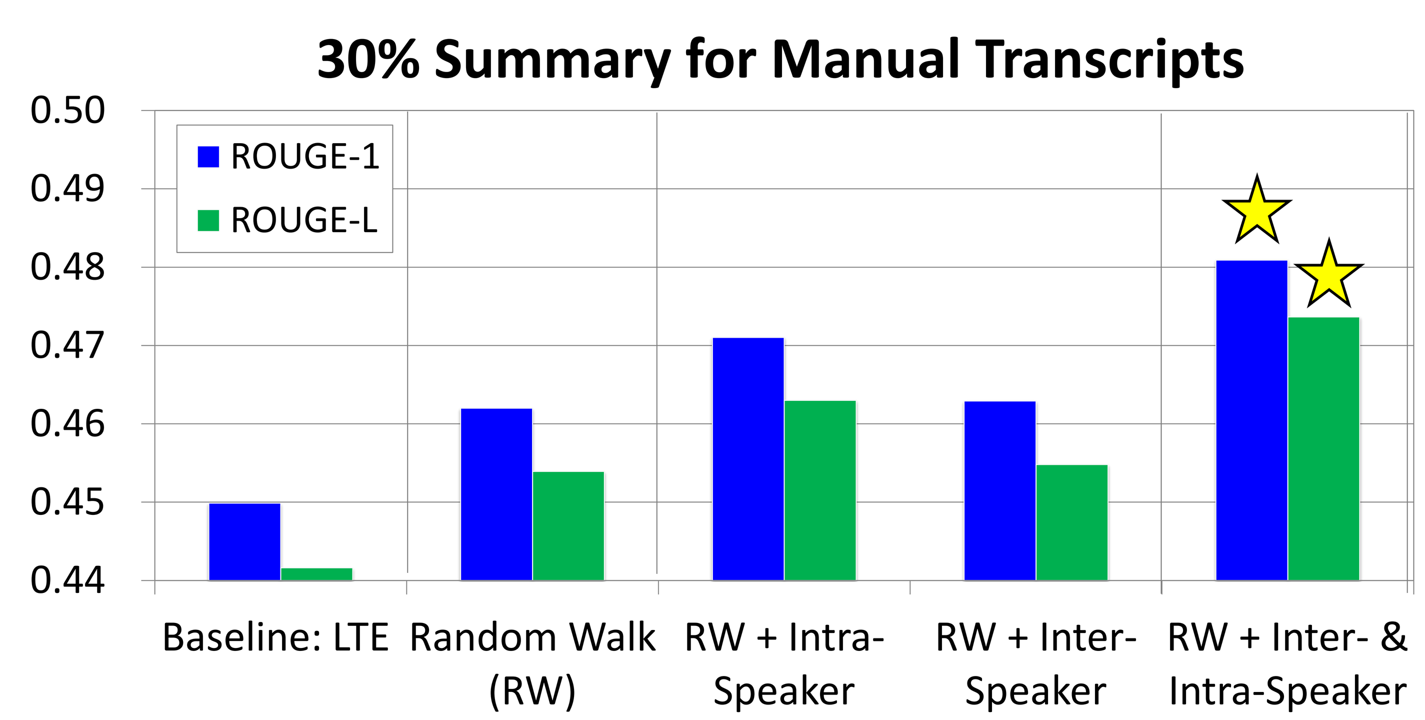
- Updated importance $\mathbf{v}=(1-\alpha)\mathbf{r}+\alpha\mathbf{P}\mathbf{v}=\left((1-\alpha)\mathbf{r}\mathbf{e}^{\mathbf{T}}+\alpha\mathbf{P}\right)\mathbf{v}=\mathbf{P}'\mathbf{v}$

  → eigenvector of P'

5. Experiments

- Dataset: 10 meetings from CMU Speech Group





6. Conclusions

- Graph-based approach can improve summarization performance using topical similarity
- Using intra-speaker topic modeling alone is useful for improving the results, because the utterances from the speaker who speaks more important utterances should be important
- Using inter-speaker topic modeling only doesn't improve the results
- Integrating intra- and inter-speaker topic modeling performs best for ASR and manual transcripts

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