Dialogue Discourse-Aware Graph Model and Data Augmentation for Meeting Summarization

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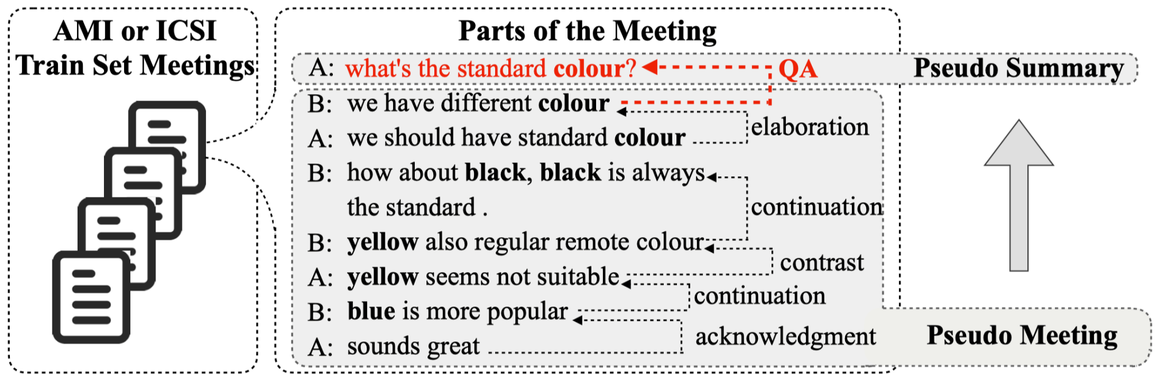
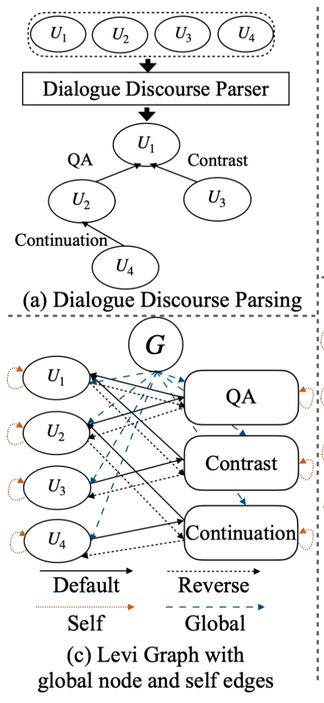
❖ Introduction

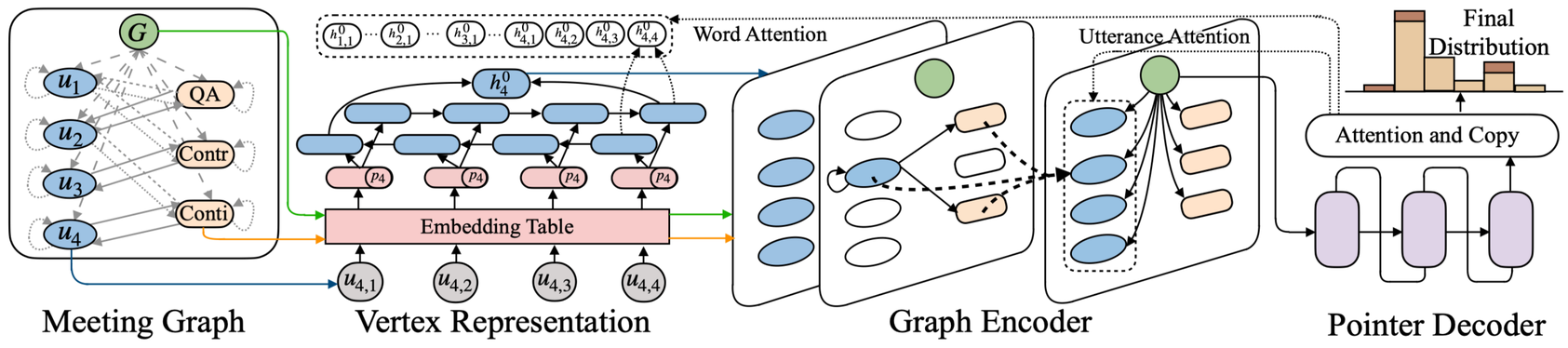
- **Meeting Summarization**
  - Distill the most important information from a recorded meeting into a short textual passage.
- **Problems**
  - Sequential text modeling: hinder the exploration of rich interactive relations between utterances.
  - Lack of sufficient training data: hinder the ability of data-hungry neural models.
- **Solution: dialogue discourse**
  - Dialogue Discourse-Aware Meeting Summarizer: model utterances and discourse in a graph interaction manner.
  - Dialogue Discourse-Aware Data Augmentation: construct a pseudo-summarization corpus based on *QA* discourse.

Parts of the Meeting
$\mathcal{A}$: What if we have a battery charger? $\mathcal{B}$: You can have neat design for it. — QA, Contrast $\mathcal{C}$: It would increase the cost. — Contrast $\mathcal{C}$: We have to change the end cost. — Continuation
Summary
$\mathcal{A}$ **asked** whether to include a battery charger. $\mathcal{B}$ **answered his question**. However, $\mathcal{C}$ **disagrees with** $\mathcal{A}$ **since it would increase the final cost.**



❖ Method





Bi-LSTM

$$\overrightarrow{\boldsymbol{h}_{i,j}} = \mathrm{LSTM}_f\left(\overrightarrow{\boldsymbol{h}_{i,j-1}}, \boldsymbol{e}_{i,j}\right)$$

$$\overleftarrow{\boldsymbol{h}_{i,j}} = \mathrm{LSTM}_b\left(\overleftarrow{\boldsymbol{h}_{i,j+1}}, \boldsymbol{e}_{i,j}\right)$$

Graph Convolution

$$g_j^{(l)} = \mathrm{sigmoid}\left(\boldsymbol{W}_{g,r}^{(l)} \boldsymbol{h}_j^{(l)}\right)$$

$$\boldsymbol{h}_i^{(l+1)} = \mathrm{ReLU}\left(\sum_{r \in \mathbb{R}_M} \sum_{v_j \in \mathbb{N}_i^r} g_j^{(l)} \frac{1}{|\mathbb{N}_i^r|} \boldsymbol{W}_r^{(l)} \boldsymbol{h}_j^{(l)}\right)$$

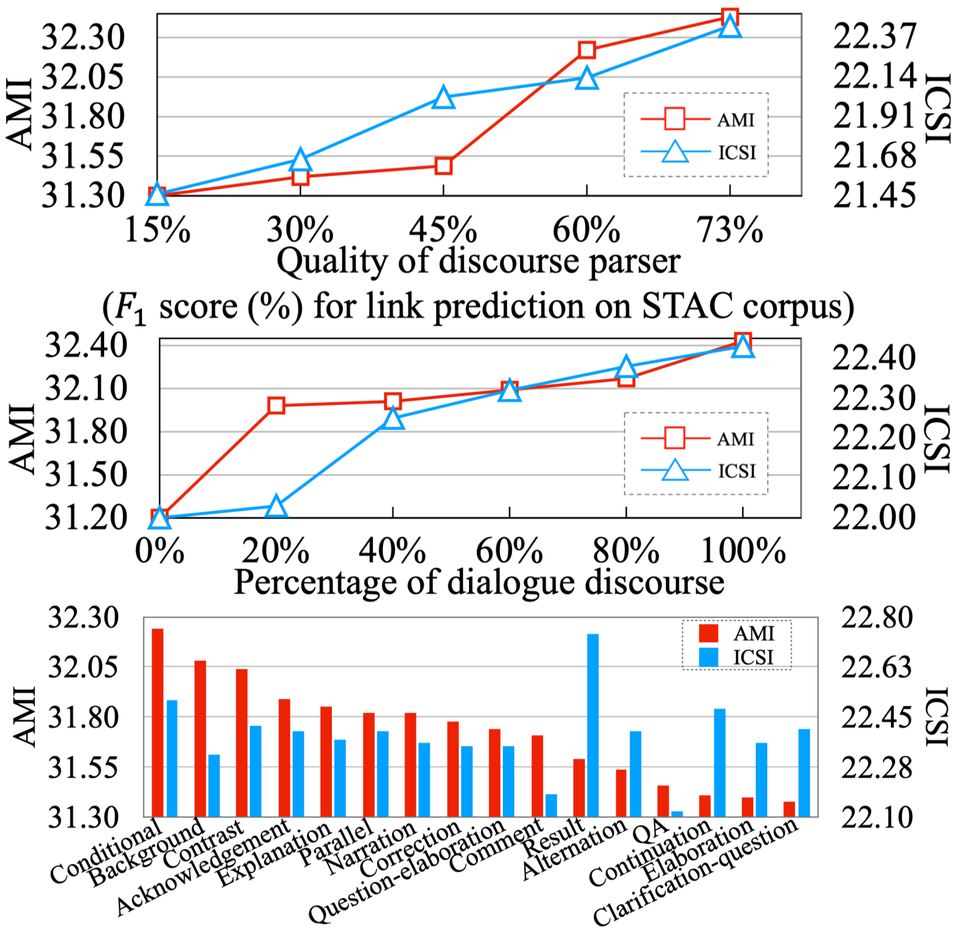
Attention

$$e_{i,j}^t = \boldsymbol{s}_t^\top \boldsymbol{W}_a \boldsymbol{h}_{i,j}^0$$

$$\boldsymbol{a}^t = \mathrm{softmax}(\boldsymbol{e}^t)$$

$$\boldsymbol{h}_t^{wl} = \sum_i \sum_j a_{i,j}^t \boldsymbol{h}_{i,j}^0$$

❖ Experiments



- **We experiment on AMI and ICSI datasets.**

	Model	AMI R-1	AMI R-2	AMI R-L	ICSI R-1	ICSI R-2	ICSI R-L
Extractive	TextRank [Mihalcea and Tarau, 2004]	35.19	6.13	15.70	30.72	4.69	12.97
	SummaRunner [Nallapati *et al.*, 2017]	30.98	5.54	13.91	27.60	3.70	12.52
Abstractive	UNS [Shang *et al.*, 2018]	37.86	7.84	13.72	31.73	5.14	14.50
	Pointer-Generator [See *et al.*, 2017]	42.60	14.01	22.62	35.89	6.92	15.67
	HRED [Serban *et al.*, 2016]	49.75	18.36	23.90	39.15	7.86	16.25
	Sentence-Gated [Goo and Chen, 2018]	49.29	19.31	24.82	39.37	9.57	17.17
	TopicSeg [Li *et al.*, 2019]	51.53	12.23	25.47	-	-	-
	HMNet [Zhu *et al.*, 2020]	52.36	18.63	24.00	**45.97**	10.14	18.54
Ours	DDAMS	51.42	20.99	24.89	39.66	10.09	17.53
	DDAMS + DDADA	**53.15**	**22.32**	**25.67**	40.41	**11.02**	**19.18**
	DDAMS + DDADA (w/o fine-tune)	28.35	4.67	14.92	25.94	4.18	13.92

❖ Resources

Paper, Code and Blog:

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