Chongqing University of Technology

ATAI
Advanced Technique of Artificial Intelligence

DARER: Dual-task Temporal Relational Recurrent Reasoning Network for Joint Dialog Sentiment Classification and Act Recognition

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Artificial

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Introduction

Utterances	Act	Sentiment
u_a: I highly recommend it. Really awesome progression and added difficulty	Statement	Positive
u_b: I never have.	Disagreement	Negative

Table 1: A dialog snippet from the Mastodon dataset.

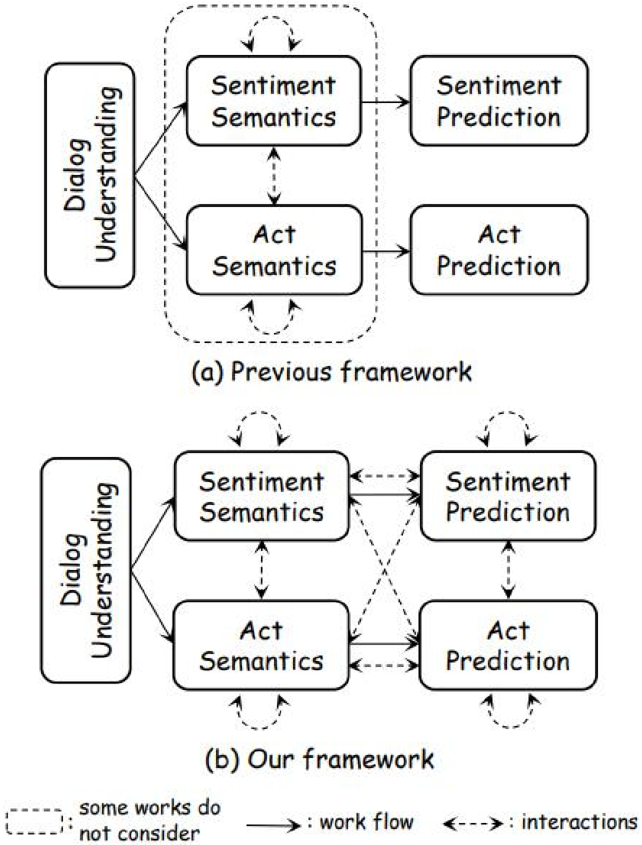


Figure 1: Illustration of previous framework and ours.

- Previous works only consider the parameter sharing and semantics-level interactions, while the label information is not integrated into the dual-task interactions.
- On the other hand, previous works do not consider the temporal relations between utterances in dual-task reasoning, while in which they play a key role.

Method

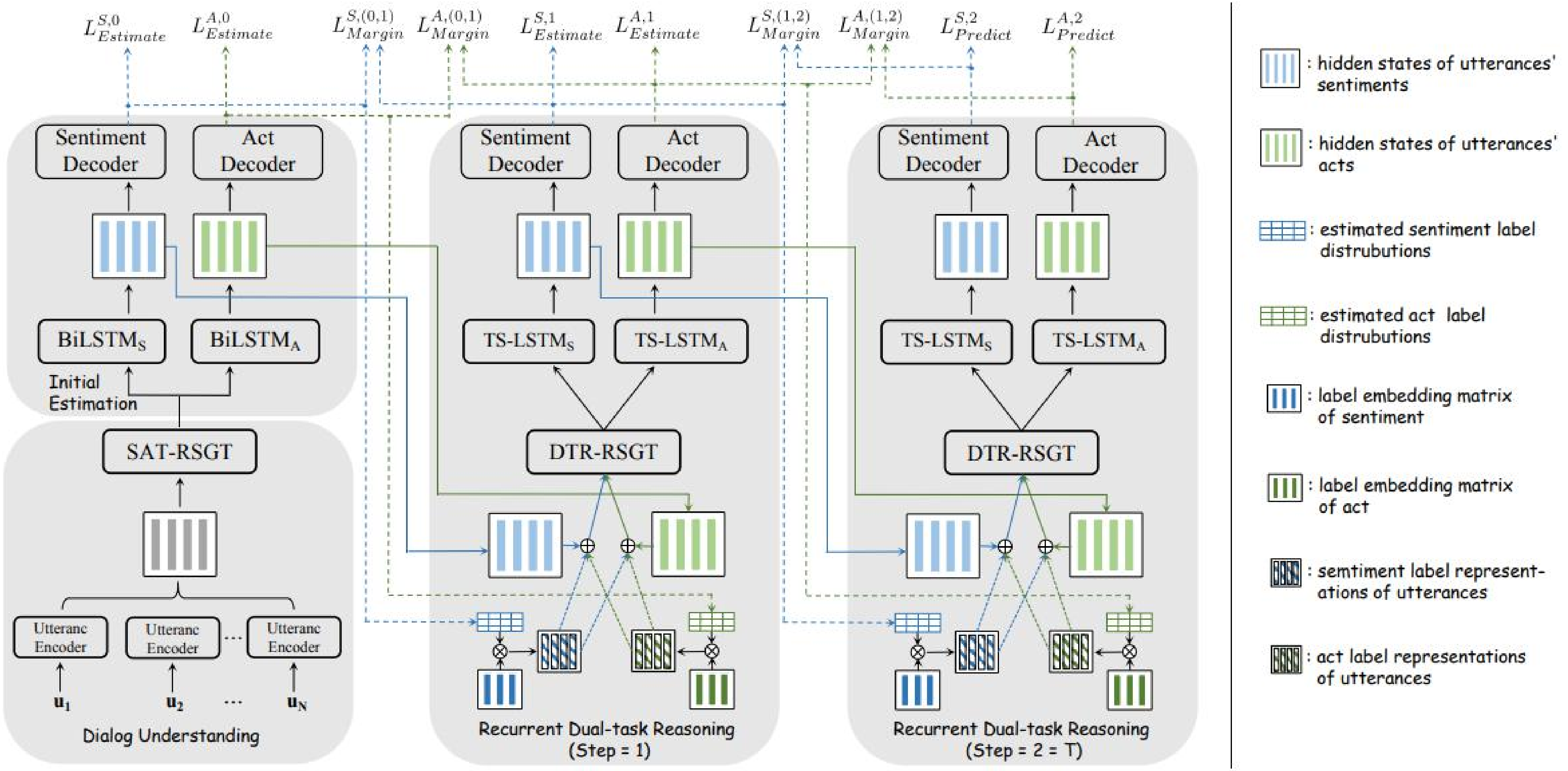
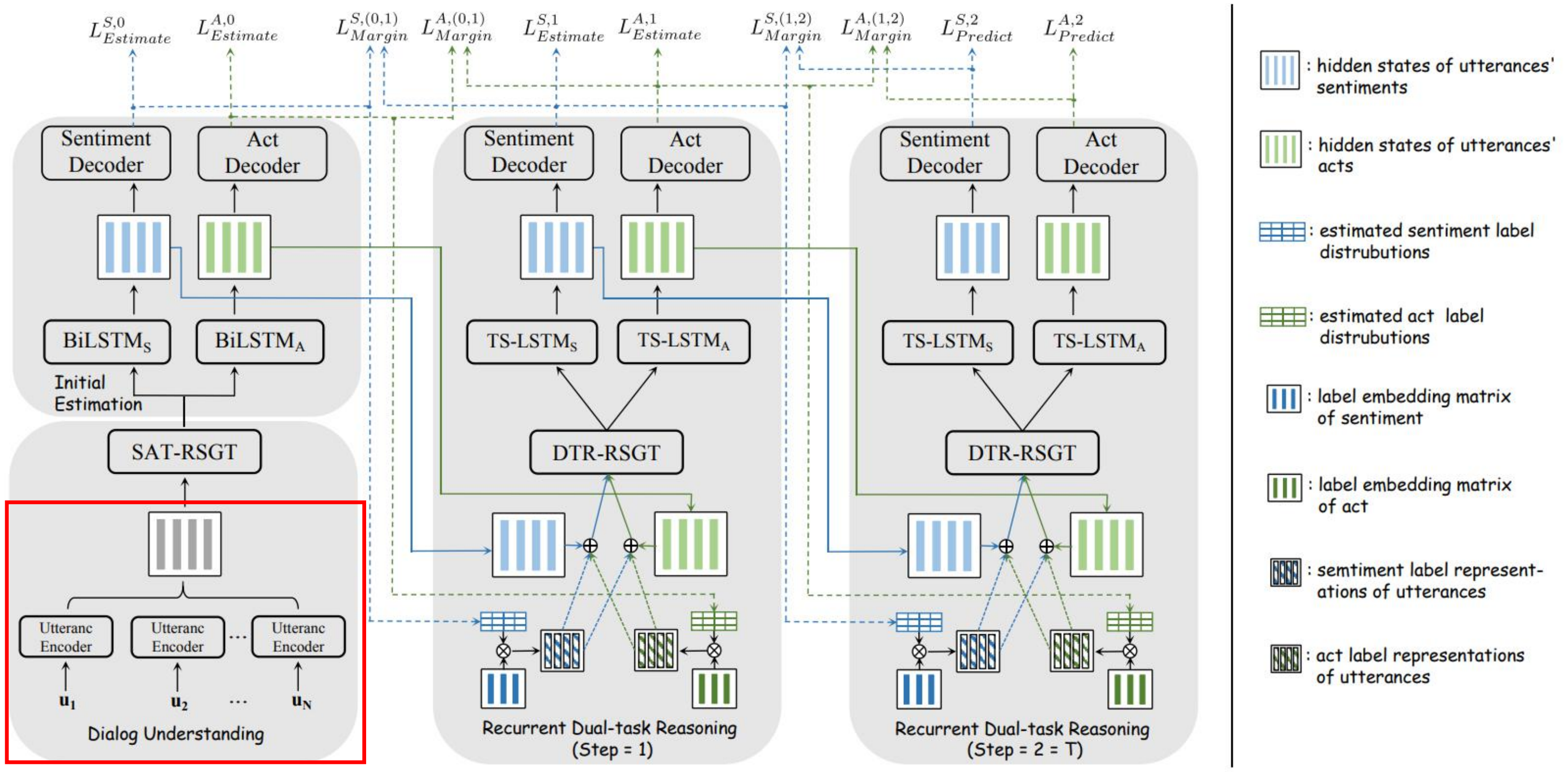


Figure 4: The network architecture of our proposed DARER model. Without loss of generality, the step number T in this illustration is set 2.

Method



Problem Definition

$$\mathcal{D} = \{u_1, u_2, ..., u_N\}$$

$$\text{dialog sentiment labels } Y^S = y_1^s, ..., y_N^s$$

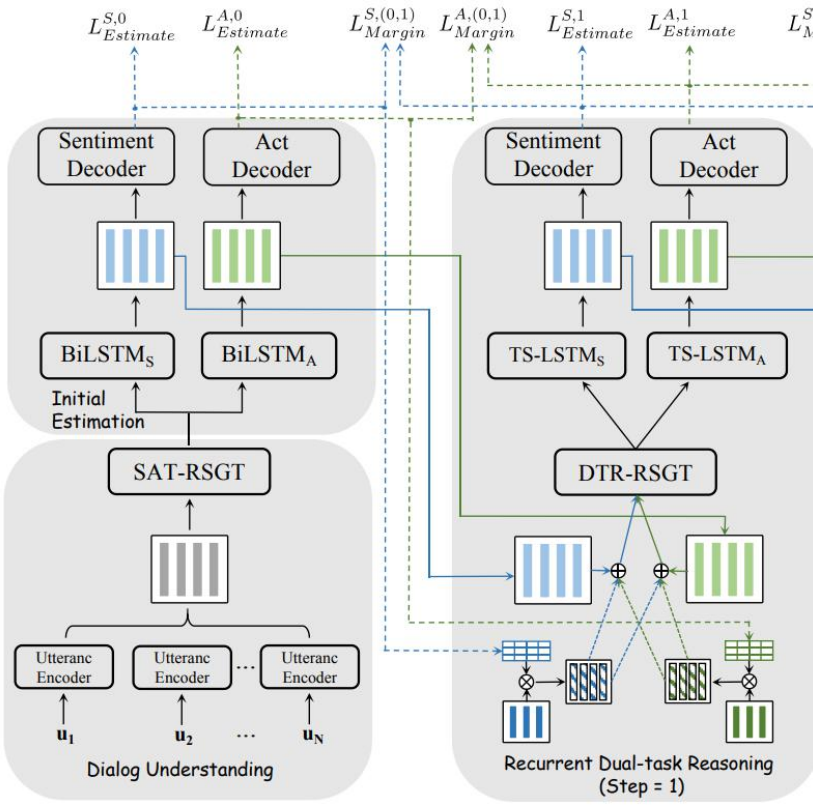
$$\text{dialog act labels } Y^A = y_1^a, ..., y_N^a$$

Utterance Encoder

$$H = (h_0, ..., h_N)$$

$$H_{u,i} = (h_{u,i}^0, ..., h_{u,i}^{l_i})$$

Method



$$M_i^l = \sum_{j \in \mathcal{N}_i} \alpha_{ij} W_{r_{ij}}^l H_j^l, \tag{5}$$

r_{ij}	1	2	3	4	5	6	7	8
$I_s(i)$	1	1	1	1	2	2	2	2
$I_s(j)$	1	1	2	2	1	1	2	2
$pos(i,j)$	$>$	$\leq$	$>$	$\leq$	$>$	$\leq$	$>$	$\leq$

Table 2: All relation types in SATG (assume there are two speakers). $I_s(i)$ indicates the speaker node i is from. $pos(i,j)$ indicates the relative position of node i and j.

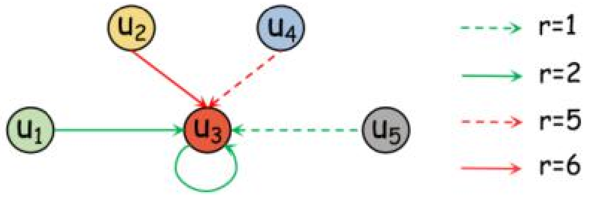


Figure 2: An example of SATG. u_1, u_3 and u_5 are from speaker 1 while u_2 and u_4 are from speaker 2. w.l.o.g, only the edges directed into u_3 node are illustrated.

Speaker-aware Temporal relation-specific graph transformations

Speaker-aware Temporal RSGT

$$\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{R})$$

$$\hat{h}_i = W_1 h_i^0 + \sum_{r \in \mathcal{R}} \sum_{j \in \mathcal{N}_i^r} \frac{1}{|\mathcal{N}_i^r|} W_1^r h_j^0 \tag{1}$$

$$\hat{H} = (\hat{h}_0, \ldots, \hat{h}_N)$$

Initial Estimation

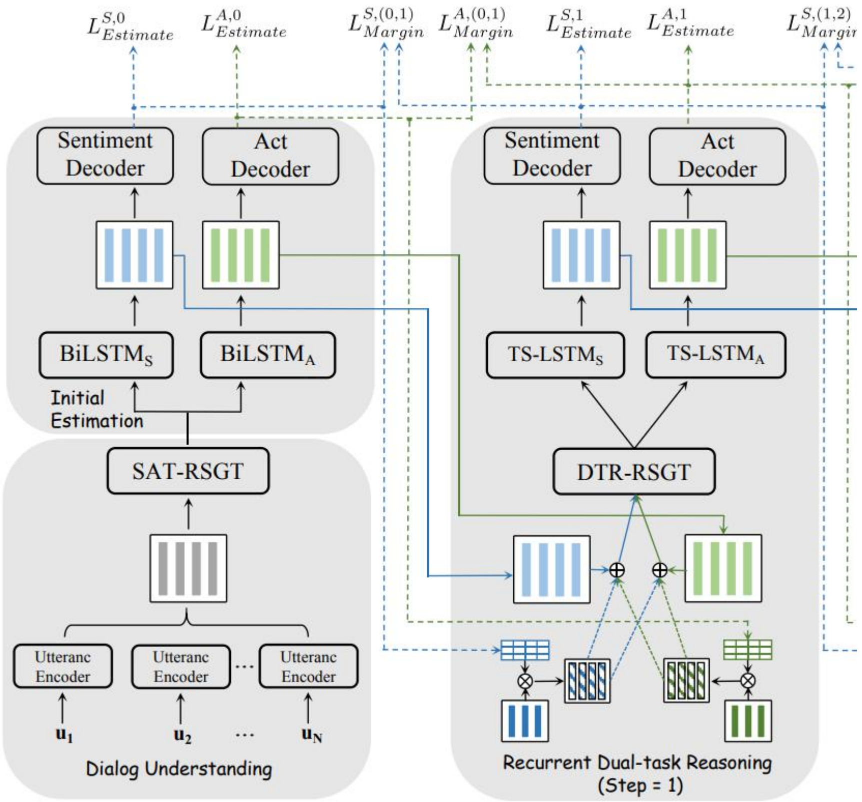
$$H_s^0 = \mathrm{BiLSTM_S}(\hat{H})$$
$$H_a^0 = \mathrm{BiLSTM_A}(\hat{H})$$

where $H_s^0 = \{h_{s,i}^0\}_{i=1}^N$ and $H_a^0 = \{h_{a,i}^0\}_{i=1}^N$

$$P_S^0 = \{P_{S,i}^0\}_{i=1}^N,\ P_A^0 = \{P_{A,i}^0\}_{i=1}^N$$
$$\begin{aligned} P_{S,i}^0 &= softmax(W_d^s h_{a,i}^0 + b_d^s) \\ &= [p_{s,i}^0[0], \ldots, p_{s,i}^0[k], \ldots, p_{s,i}^0(|\mathcal{C}_s|-1)] \quad (2) \\ P_{A,i}^0 &= softmax(W_d^a h_{s,i}^0 + b_d^a) \\ &= [p_{a,i}^0[0], \ldots, p_{a,i}^0[k], \ldots, p_{a,i}^0(|\mathcal{C}_a|-1)] \end{aligned}$$

where W_d^* and b_d^* are weight matrices and biases, $\mathcal{C}_s$ and $\mathcal{C}_a$ are sentiment class set and act class set.

Method



r'_{ij}	1	2	3	4	5	6	7	8	9	10	11	12
$I_t(i)$	S	S	S	S	S	S	A	A	A	A	A	A
$I_t(j)$	S	S	S	A	A	A	S	S	S	A	A	A
$pos(i,j)$	$<$	$=$	$>$	$<$	$=$	$>$	$<$	$=$	$>$	$<$	$=$	$>$

Table 3: All relation types in DRTG. $I_t(i)$ indicates that node i is a sentiment (S) node or act (A) node.

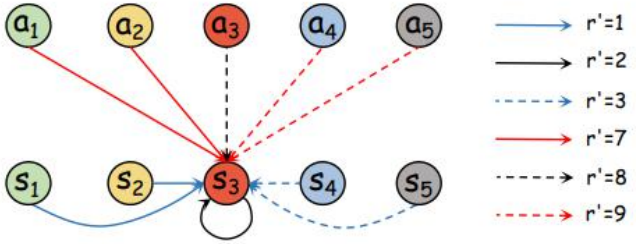


Figure 3: An example of DRTG. s_i and a_i respectively denote the node of DAC task and DAR task. w.l.o.g, only the edges directed into s_3 are illustrated.

Recurrent Dual-task Reasoning

- **Projection of Label Distribution**

$$e^t_{s,i} = \sum_{k=0}^{|\mathcal{C}_s|-1} p^{t-1}_{s,i}[k] \cdot v^k_s$$
$$e^t_{a,i} = \sum_{k'=0}^{|\mathcal{C}_a|-1} p^{t-1}_{a,i}[k'] \cdot v^{k'}_a \quad (3)$$

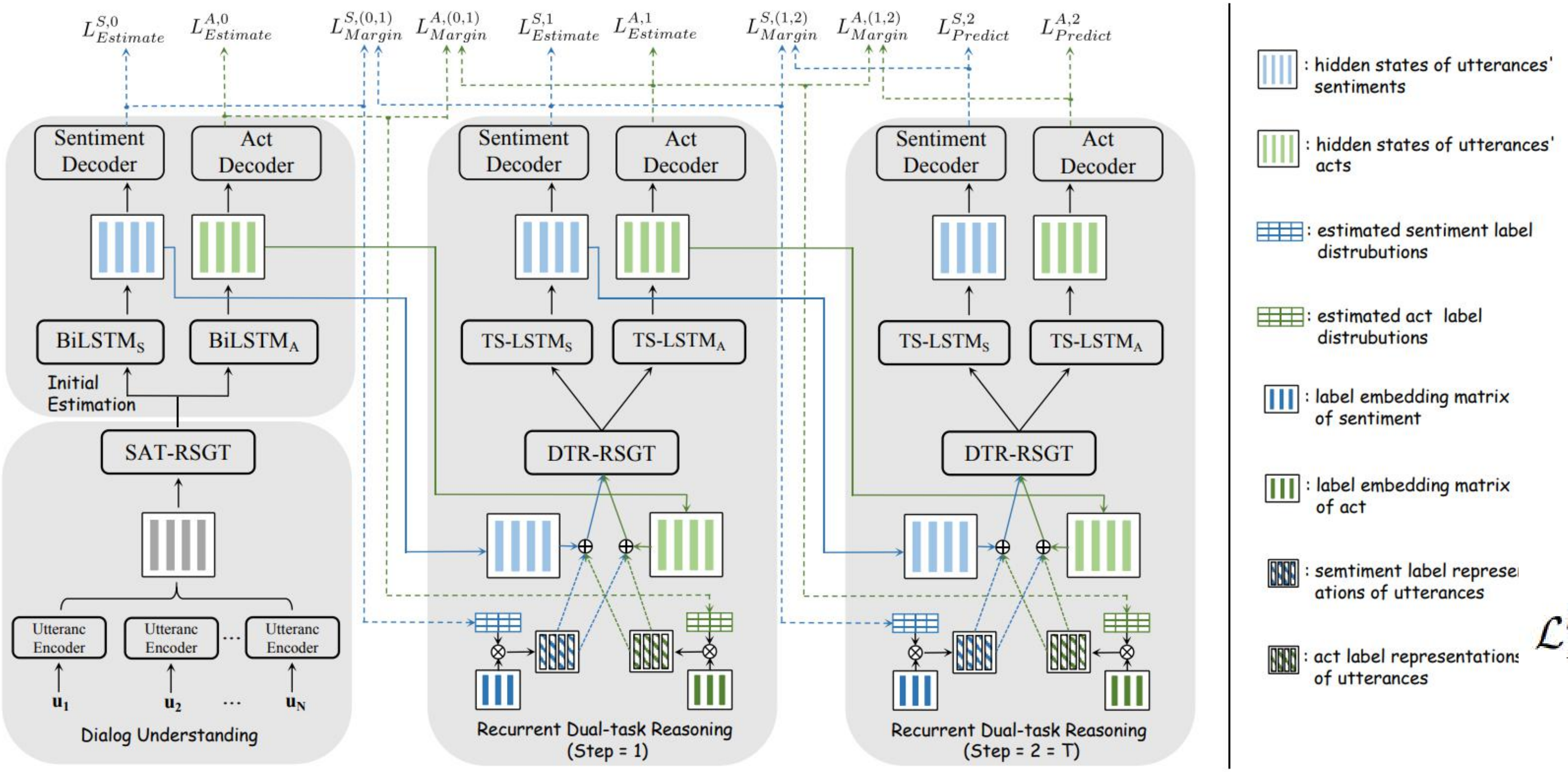
where v^k_s and $v^{k'}_a$ are the label embeddings of sentiment class k and act class k', respectively.

$$\hat{h}^t_{s,i} = h^{t-1}_{s,i} + e^t_{s,i} + e^t_{a,i}$$
$$\hat{h}^t_{a,i} = h^{t-1}_{a,i} + e^t_{s,i} + e^t_{a,i} \quad (4)$$

$$\overline{h}^t_i = W_2 \hat{h}^t_i + \sum_{r \in \mathcal{R}'} \sum_{j \in \mathcal{N}^{r'}_i} \frac{1}{|N^{r'}_i|} W^r_2 \hat{h}^t_j \quad (5)$$

$$H^t_s = \mathrm{TS\text{-}BiLSTM_S}(\overline{H}^t_s)$$
$$H^t_a = \mathrm{TS\text{-}BiLSTM_A}(\overline{H}^t_a) \quad (6)$$

Method



Estimate Loss

$$\mathcal{L}^{S,t}_{Estimate} = \sum_{i=1}^{N} \sum_{k=0}^{|\mathcal{C}_s|-1} y^{k}_{s,i} \log\left(p^{t}_{s,i}[k]\right) \qquad (7)$$

Margin Loss

$$\mathcal{L}^{S,(t,t-1)}_{Margin} = \sum_{i=1}^{N} \sum_{k=0}^{|\mathcal{C}_s|-1} y^{k}_{s,i} \max(0, p^{t-1}_{s,i}[k] - p^{t}_{s,i}[k]) \qquad (8)$$

Constraint loss

$$\mathcal{L}^{S}_{Constraint} = \sum_{t=0}^{T-1} \mathcal{L}^{S,t}_{Estimate} + \gamma * \sum_{t=1}^{T} \mathcal{L}^{S,(t,t-1)}_{margin} \qquad (9)$$

Prediction loss

$$\mathcal{L}^{S}_{Prediction} = \sum_{i=1}^{N} \sum_{k=0}^{|\mathcal{C}_s|-1} y^{k}_{s,i} \log\left(p^{T}_{s,i}[k]\right) \qquad (11)$$

Final Training Objective

$$\mathcal{L}^{S} = \mathcal{L}^{S}_{Prediction} + \mathcal{L}^{S}_{Constraint} \qquad (10)$$

$$\mathcal{L} = \mathcal{L}^{S} + \mathcal{L}^{A} \qquad (12)$$

Experiments

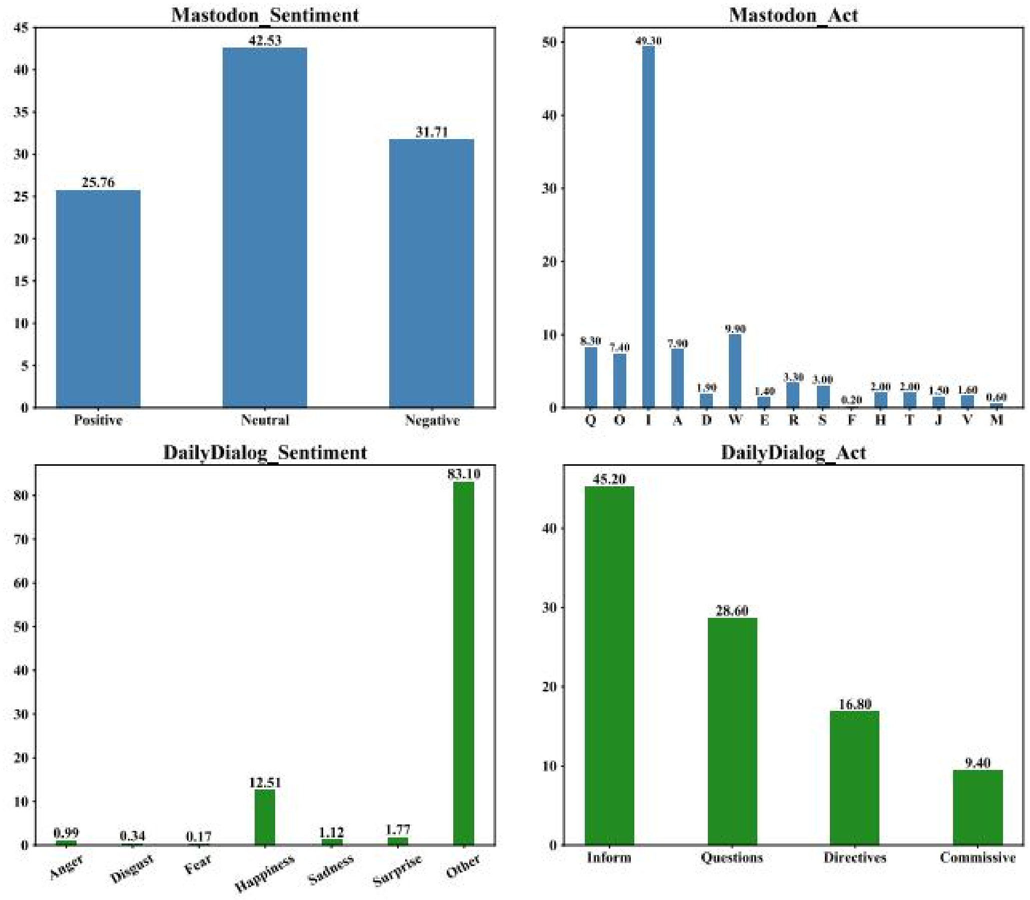


Figure 5: Illustration of class distributions.

Experiments

Models	Mastodon						DailyDialog					
	DSC			DAR			DSC			DAR		
	P(%)	R(%)	F1(%)	P(%)	R(%)	F1(%)	P(%)	R(%)	F1(%)	P(%)	R(%)	F1(%)
JointDAS	36.1	41.6	37.6	55.6	51.9	53.2	35.4	28.8	31.2	76.2	74.5	75.1
IIIM	38.7	40.1	39.4	56.3	52.2	54.3	38.9	28.5	33.0	76.5	74.9	75.7
DCR-Net	43.2	47.3	45.1	60.3	56.9	58.6	56.0	40.1	45.4	79.1	79.0	79.1
BCDCN	38.2	62.0	45.9	57.3	61.7	59.4	55.2	45.7	48.6	80.0	80.6	80.3
Co-GAT	44.0	53.2	48.1	60.4	60.6	60.5	65.9	45.3	51.0	81.0	78.1	79.4
Co-GAT*	45.40 $\pm$2.31	48.11 $\pm$2.91	46.47 $\pm$0.37	62.55 $\pm$0.46	58.66 $\pm$1.71	60.54 $\pm$1.10	58.04 $\pm$0.84	44.65 $\pm$0.36	48.82 $\pm$0.22	79.14 $\pm$0.40	79.71 $\pm$0.16	79.39 $\pm$0.14
DARER	**56.04**† $\pm$0.85	**63.33**† $\pm$0.30	**59.59**† $\pm$0.70	**65.08**‡ $\pm$1.25	**61.88**† $\pm$0.37	**63.43**† $\pm$0.85	**59.96**‡ $\pm$1.25	**49.51**† $\pm$1.33	**53.42**† $\pm$0.18	**81.39**† $\pm$0.55	**80.80**‡ $\pm$0.43	**81.06**† $\pm$0.04

Table 4: Experiment results. * denotes we reproduce the results using official code. $\pm$ denotes standard deviation. † denotes that our DARER significantly outperforms Co-GAT with $p < 0.01$ under t-test and ‡ denotes $p < 0.05$.

Experiments

Variants	Mastodon		DailyDialog	
	DSC	DAR	DSC	DAR
DARER	**59.59**	**63.43**	**53.42**	**81.39**
w/o Label Embeddings	56.76	62.15	50.64	79.87
w/o Harness Loss	56.22	61.99	49.94	79.76
w/o SAT-RSGT	57.37	62.96	50.25	80.52
w/o DTR-RSGT	56.69	61.69	50.11	79.76
w/o TS-LSTMs	56.30	61.49	51.61	80.33
w/o Tpl Rels in SATG	58.23	62.21	50.99	80.70
w/o Tpl Rels in DRTG	57.22	62.15	50.52	80.28

Table 5: Results of ablation experiments on F1 score.

Experiments

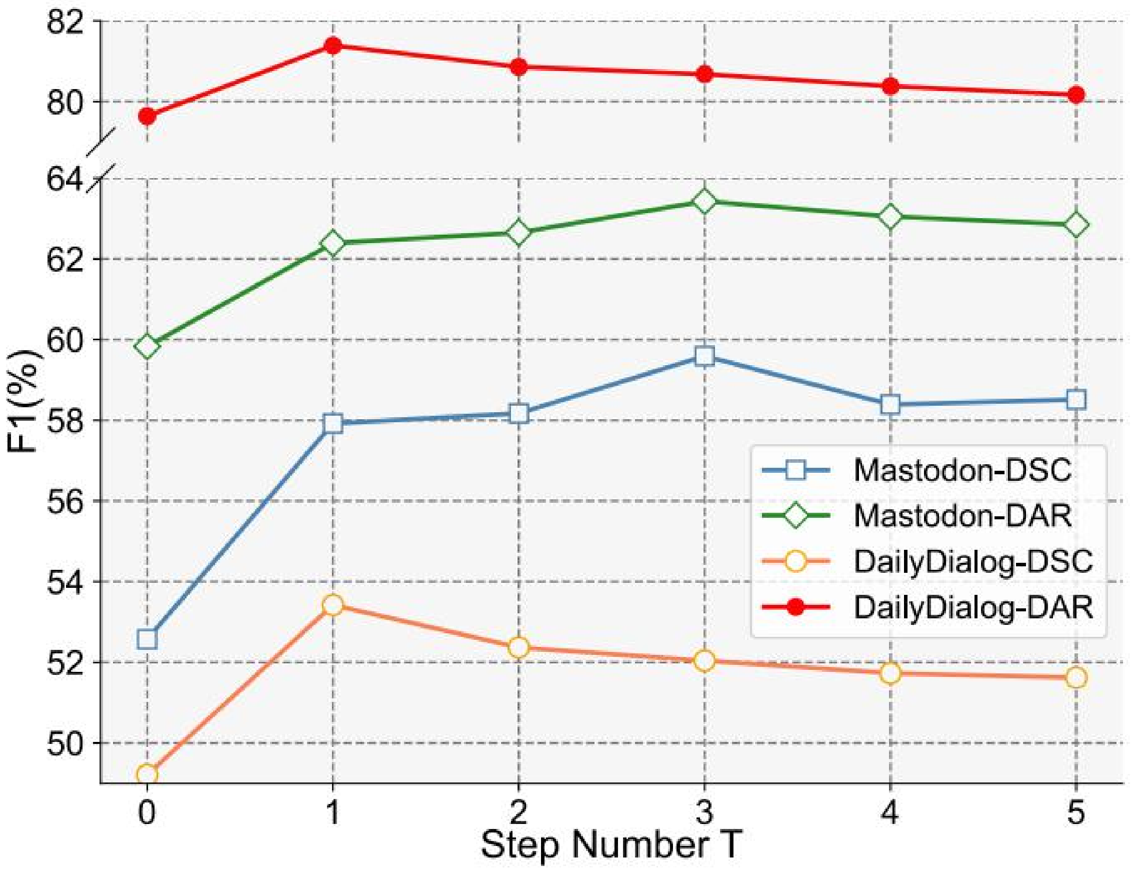


Figure 6: Performances of DARER over different T.

Models		Mastodon DSC P(%)	DSC R(%)	DSC F1(%)	Mastodon DAR P(%)	DAR R(%)	DAR F1(%)
BERT	+ Linear	61.79	61.09	60.60	70.20	67.49	68.82
	+ Co-GAT	66.03	58.13	61.56	70.66	67.62	69.08
	+ DARER	65.98	67.39	**66.42**	73.82	71.67	**72.73**
RoBERTa	+ Linear	57.83	60.54	57.83	62.49	61.93	62.20
	+ Co-GAT	61.28	57.25	58.26	66.46	64.01	65.21
	+ DARER	61.36	67.27	**63.66**	70.87	68.68	**69.75**
XLNet	+ Linear	61.42	67.80	63.35	67.31	63.04	65.09
	+ Co-GAT	64.01	65.30	63.71	67.19	64.09	65.60
	+ DARER	68.05	69.47	**68.66**	72.04	69.63	**70.81**

Table 6: Results based on different PTLM encoders.

Experiments

Models	Number of Parameters	Training Time per Epoch	GPU Memory	Avg. F1
Co-GAT	6.93M	2.35s	2007MB	53.66%
DARER	2.50M	2.20s	1167MB	61.51%
Improve	**-63.92%**	**-6.38%**	**-41.85%**	**14.63%**

Table 7: Comparison with SOTA on different aspects.