



Topic-Aware Response Generation in Task-Oriented Dialogue with Unstructured Knowledge Access

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code: <https://github.com/huawei-noah/noah-research/tree/NLP/TARG>

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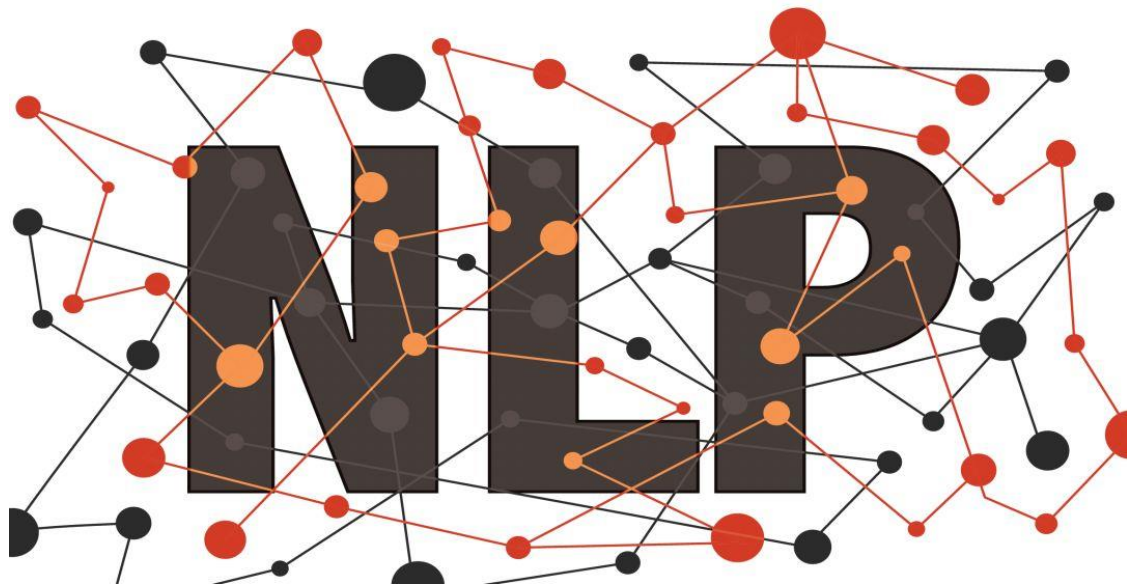
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Reported by Junhao Cao



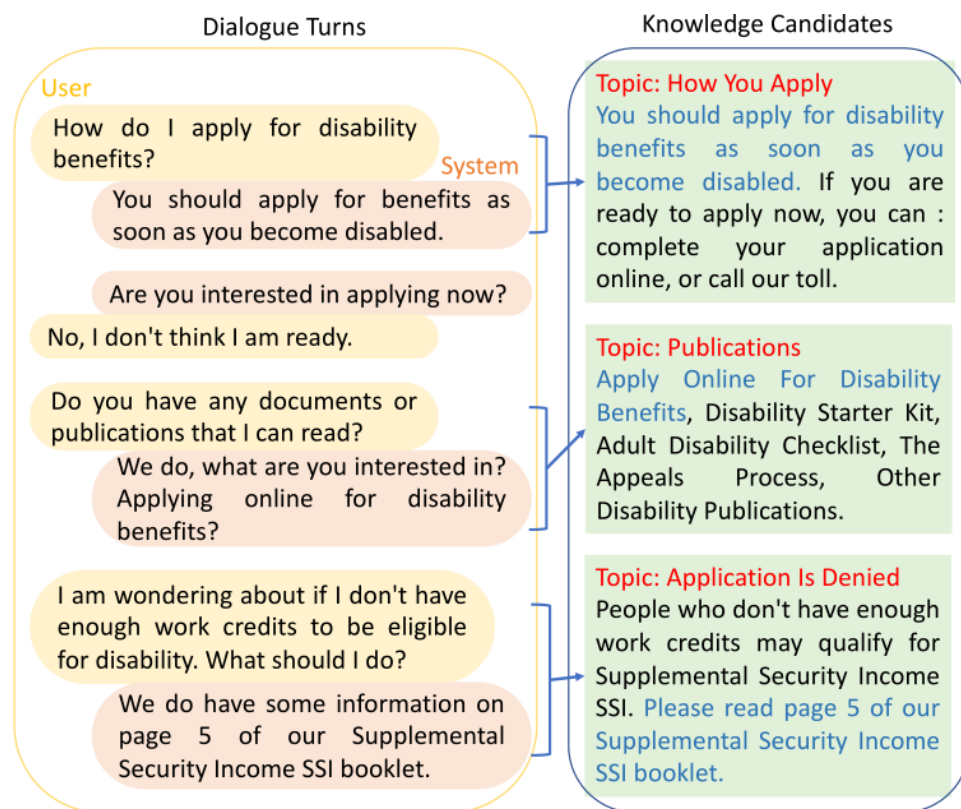
NATURAL LANGUAGE PROCESSING



- 1. Introduction**
- 2. Method**
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Introduction



we can observe that **as the knowledge selection shifts**, a corresponding **shift occurs between topics**. Previous work has not actively exploited this, but we posit that the topic shifts can provide signals that help making knowledge selection.

Figure 1: An example of knowledge-grounded dialogue.

Method

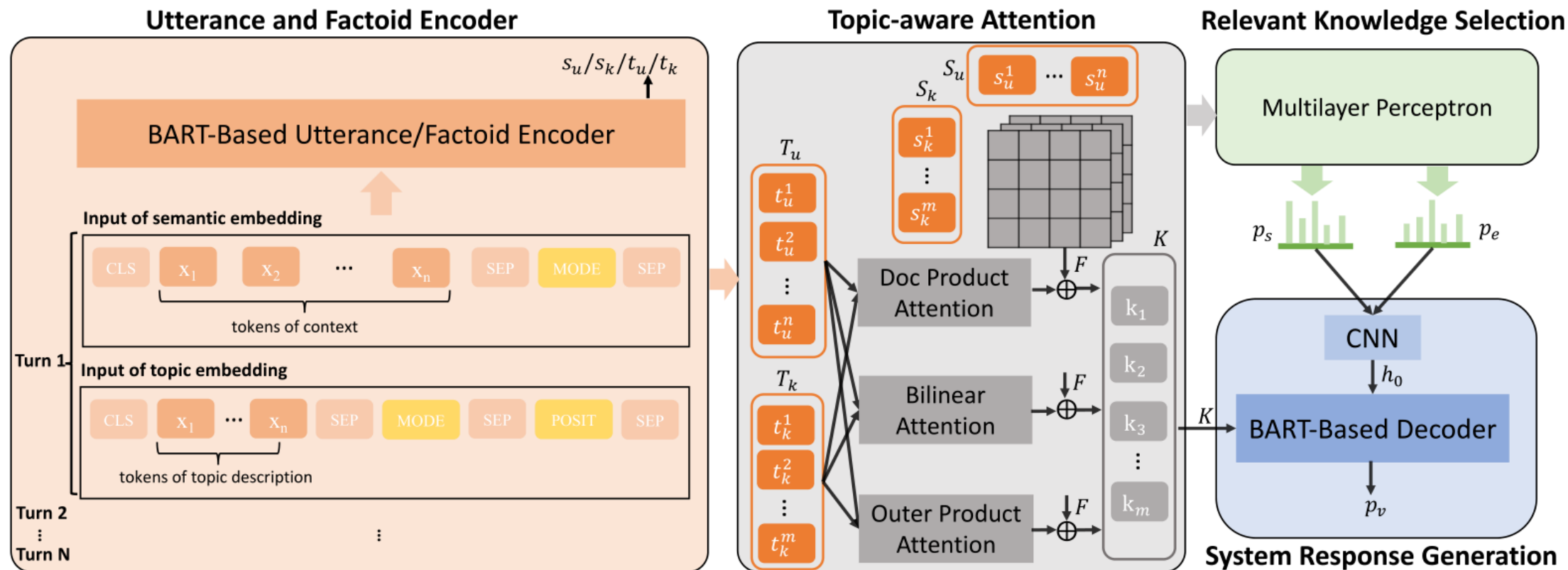


Figure 2: Overview of Topic-Aware Response Generation (TARG).

Method

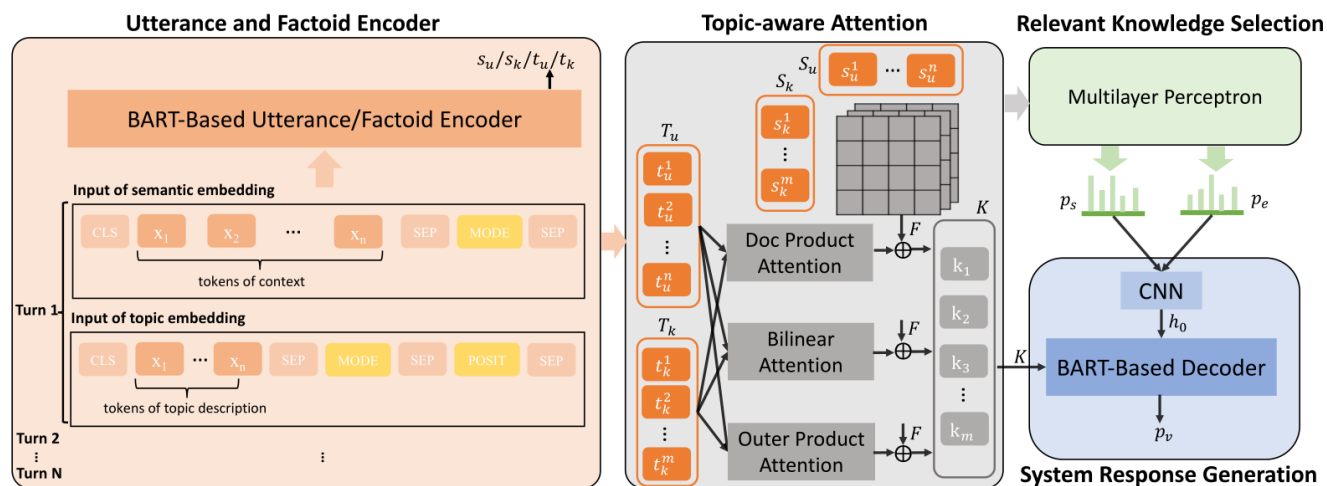


Figure 2: Overview of Topic-Aware Response Generation (TARG).

Utterance and Factoid Encoder

$$X = ([CLS], x_1, \dots, x_N, [SEP], [MODE], [SEP])$$

[MODE] is one of [SYS]/[USER]/[KLG]

$$T = ([CLS], x_1, \dots, x_N, [SEP], [MODE], [SEP], [POSIT], [SEP])$$

Method

Topic-aware Attention

Dot Product:

$$A_d^i = \text{softmax}(\exp([t_u^j, t_k^i]w_d), \forall t_u^j \in T_u) \quad (1)$$

Bilinear:

$$A_b^i = \text{softmax}(\exp(t_u^j W_b t_k^{i\top}), \forall t_u^j \in T_u) \quad (2)$$

Outer Product:

$$A_o^i = \text{softmax}(\exp((t_u^j \times t_k^i)w_o), \forall t_u^j \in T_u) \quad (3)$$

$$F_{i,j} = v_f^\top \tanh(s_u^j W_f s_k^{i\top} + b_f) \quad (4)$$

$$k_i = [A_d^{i\top} F_i, A_b^{i\top} F_i, A_o^{i\top} F_i] \quad (5)$$

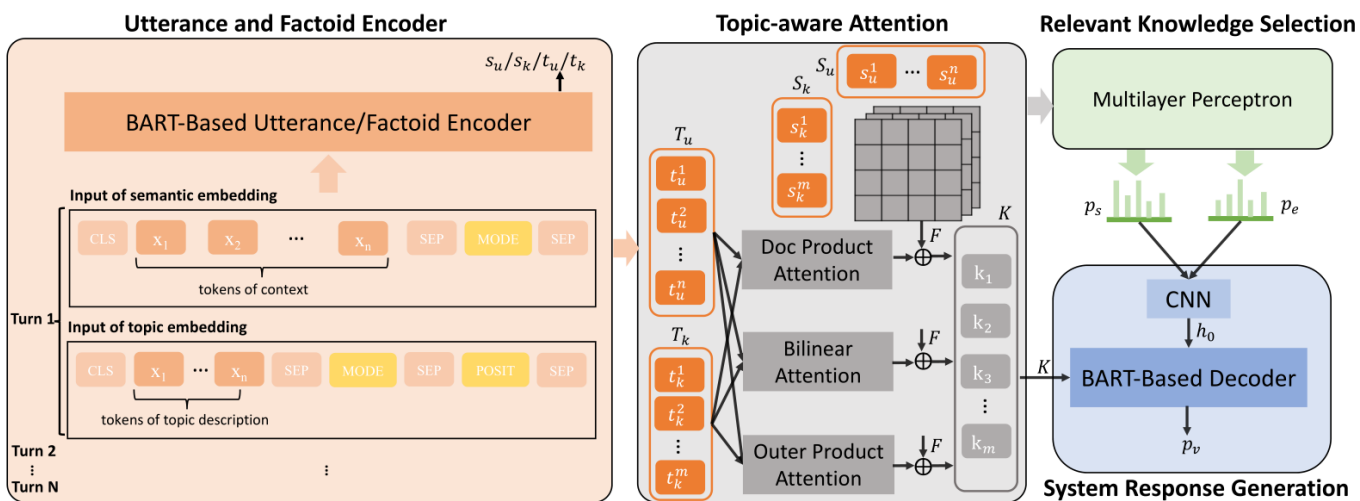


Figure 2: Overview of Topic-Aware Response Generation (TARG).

Method

Relevant Knowledge Selection

$$p^s = \text{softmax}(W_s^\top K + b_s^\top), \quad (6)$$

$$p^e = \text{softmax}(W_e^\top K + b_e^\top), \quad (7)$$

System Response Generation

$$f = \text{CNN}(K_{:,s:e}), \quad (8)$$

$$h_t = \text{BART}(w_{t-1}, h_{t-1}, K_{:,s:e}). \quad (9)$$

$$p_v = \text{softmax}(VW_v h_t + b_v), \quad (10)$$

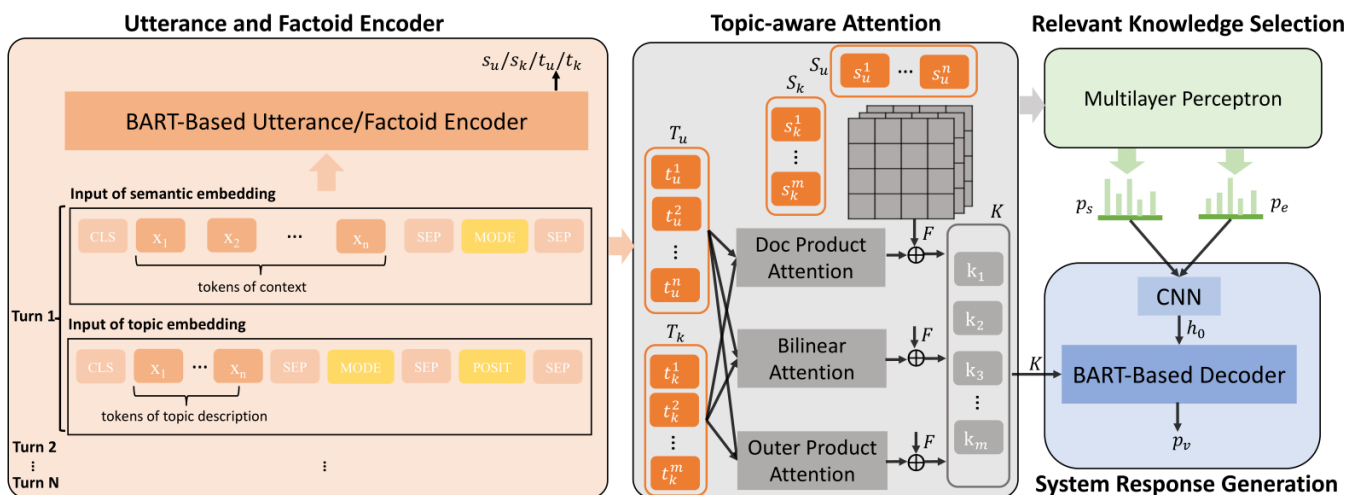


Figure 2: Overview of Topic-Aware Response Generation (TARG).

Method

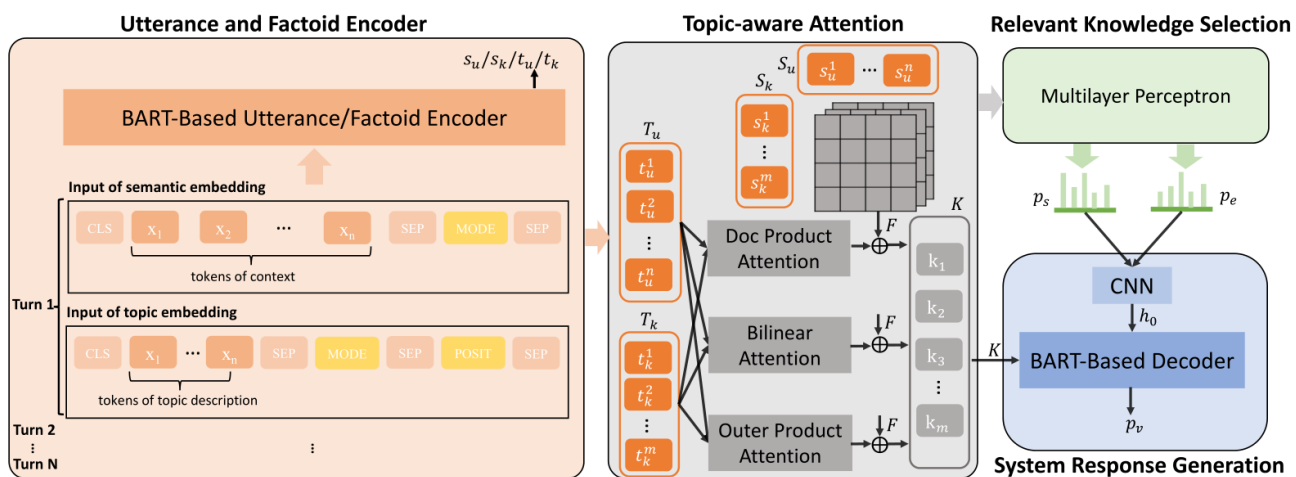


Figure 2: Overview of Topic-Aware Response Generation (TARG).

$$\mathcal{L}_s = -\frac{1}{NM} \sum_{n=0}^N \sum_{m=0}^M [\log(p_{y_{nm}^s}^s) + \log(p_{y_{nm}^e}^e)], \quad (11)$$

$$\mathcal{L}_g = -\frac{1}{NM} \sum_{n=0}^N \sum_{m=0}^M \log P(Y_{nm} | D_{nm}, K_{nm}), \quad (12)$$

$$\mathcal{L} = \lambda \cdot \mathcal{L}_s + (1 - \lambda) \cdot \mathcal{L}_g, \quad (13)$$



Experiment

Model	Knowledge Selection		Response Generation
	EM	F1	BLEU-4
Base-D2D	37.2	52.9	17.7
Base-D2D-ST	27.6	35.2	12.1
JARS	42.1	57.8	-
CAiRE	45.7	60.1	22.3
RWTH	46.6	62.8	24.4
TARG	49.8	66.4	28.6

Table 3: Performance of TARG and related work on Doc2Dial. **Bold** denotes best results in that metric.

Experiment

Model	Knowledge Selection		Response Generation						
	MRR@5	Recall@5	BLEU-1	BLEU-2	BLEU-3	BLEU-4	ROUGE-1	ROUGE-2	ROUGE-L
Base-DSTC	0.726	0.877	0.303	0.173	0.100	0.065	0.338	0.136	0.303
Base-DSTC-ST	0.612	0.743	0.251	0.132	0.083	0.047	0.262	0.104	0.244
KDEAK	0.853	0.896	0.355	0.230	0.153	0.104	0.397	0.190	0.357
RADGE	0.937	0.966	0.350	0.217	0.135	0.089	0.393	0.175	0.355
EGR	0.894	0.934	0.361	0.226	0.140	0.096	0.397	0.179	0.353
TARG	0.935	0.972	0.366	0.224	0.156	0.111	0.408	0.183	0.360

Table 4: Performance of TARG and related work on the DSTC9 dataset. **Bold** denotes best results in that metric.

Experiment

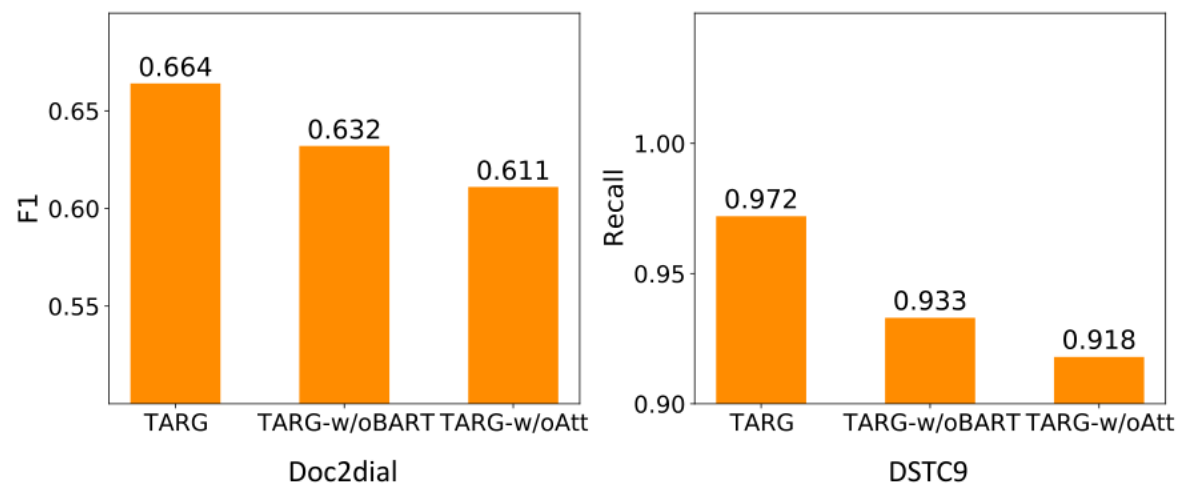


Figure 3: Ablation study for knowledge selection.

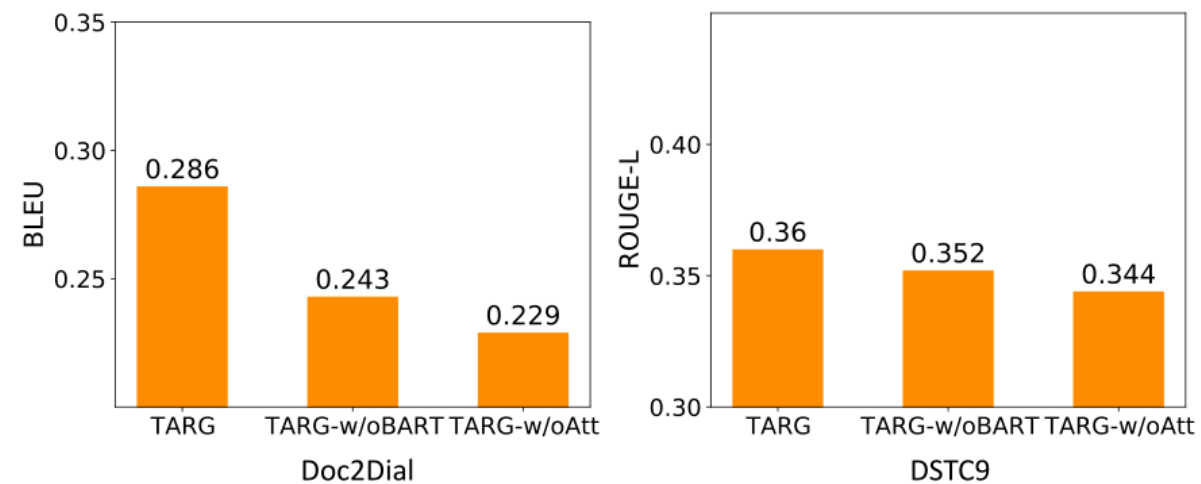


Figure 4: Ablation study for response generation.

Experiment

Dialogue History Turns		Knowledge Candidates (Factoids)	
<i>U1</i>	<u>U</u> : I wanted to know about career options.		
<i>S1</i>	<u>S</u> : Do you love working with animals?		
<i>U2</i>	<u>U</u> : No, what else you got?		
<i>S2</i>	<u>S</u> : Do you like working with computers?		
<i>U3</i>	<u>U</u> : I use them but wouldn't care to work on computer related things. Do you have any info for the parents to look at?	<i>T1</i>	Exploring Your Career Options Love working with animals? How about computers? Find possible careers to match your interests.
<i>S3</i>	<u>S</u> : Is this information for a parent that is planning ahead for a child's higher education?		
<i>U4</i>	<u>U</u> : yes it is.	<i>T2</i>	Resources for Parents of Students Are you a parent planning ahead for your child s higher education? Review our resources for parents to learn more about saving early, and finding tax breaks.
<i>S4</i>	<u>S</u> : We have resources for parents to learn more about saving early, and finding tax breaks.		
<i>U5</i>	<u>U</u> : Do you have any info on how college can help me?	<i>T3</i>	Preparing for College Check out Reasons to Attend a College or Career School. Learning About Budgeting Resources for Parents of Students.
Generated Response			
<i>Ground Truth</i>	Yes, you can look at our Reasons to Attend a College or Career School section.		
<i>TARG</i>	Please look at Reasons to Attend a College or Career School.		
<i>RWTH</i>	Yes, Budgeting Resources for Parents of Students.		
<i>Doc2Dial-baseline</i>	Review our resources for parents.		

Figure 5: Case study on Doc2Dial. Dialogue history turns are grounded to knowledge candidates of the same color.

Experiment

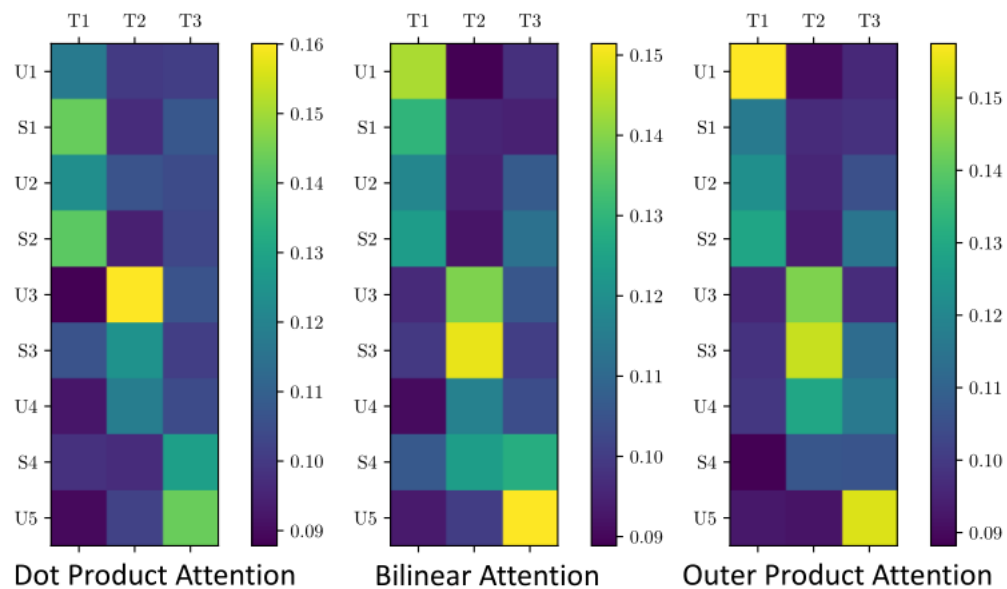


Figure 6: Visualization of learned topic-aware attention of dialogue history utterances U-X and S-X (for user and system utterance) for each topic T-X in the example in Figure 5. Lighter spots mean higher attention scores.

Model	Knowledge Selection		Response Generation
	EM	F1	BLEU
TARG-dot	0.468	0.642	0.261
TARG-bilinear	0.481	0.652	0.268
TARG-outer	0.489	0.655	0.275
TARG	0.498	0.664	0.286

Table 5: Ablation over different attention mechanisms.



Thank you!



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