SEntNet: Source-aware Recurrent Entity Network for Dialogue Response Selection

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1.1 Task-oriented Dialogue Systems (TDSs)

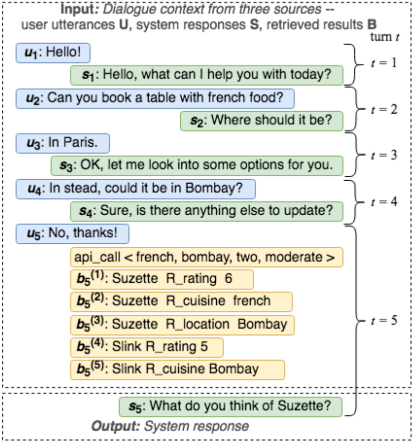
Task-oriented DSs → complete certain tasks or goals on specific domain (e.g., *finding restaurants*)

User: I'm looking for an affordable restaurant
System: How about Thai food?
User: Yes please, in central Cambridge
System: The House serves cheap Thai food
User: Where is it?
System: The House is at 106 Regent Street

Non-task-oriented DSs → provide reasonable responses & entertainment on open domain (e.g., chatbots)

User: Hey, do you know Monica?
System: Yes, I found her via AM leaks. She has the same hobbies as I and loves to meet in secluded area within.
User: Seriously?
System: Nope.
...

1.2 Dialogue Response Selection in TDSs



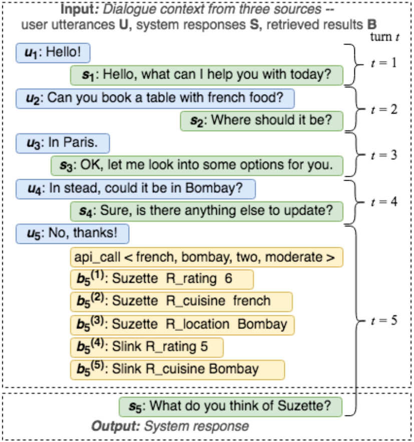
Traditionally,

- **Given**: a dialogue context $\mathbb{C}_t = (u_1, s_1, \ldots, u_t, s_t, [b_t^1, b_t^2, \ldots, b_t^\lambda])$
- **Goal**: select a response s_t from candidates by

$$\psi_\Theta(\mathbb{C}_t) \rightarrow s_t. \tag{1}$$

- **Problem**. Obtaining the important information from a complex, long dialogue context is challenging.

1.3 Motivation

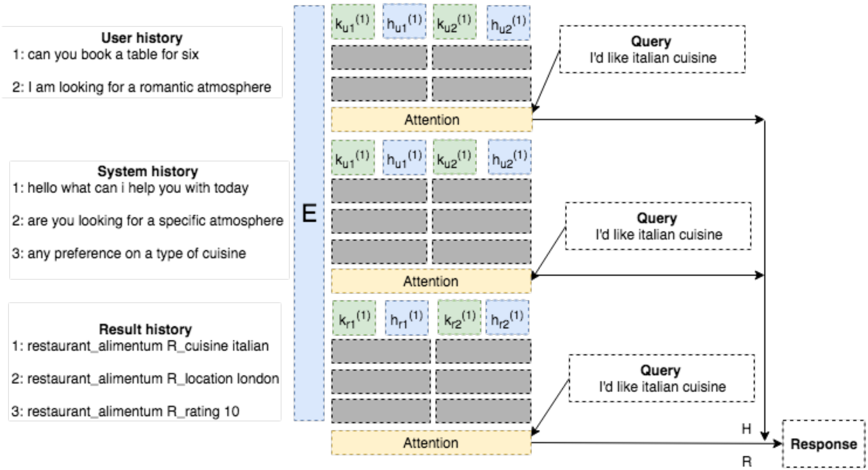


- **Given**: a dialogue context $(\mathbb{U}_t, \mathbb{S}_{t-1}, \mathbb{B}_t)$:
  - $\mathbb{U}_t = (u_1,\ u_2,\ \ldots,\ u_t)$ are user utterances;
  - $\mathbb{S}_{t-1} = (s_1,\ s_2,\ \ldots,\ s_{t-1})$ are system responses; and
  - $\mathbb{B}_t = (b_t^1, b_t^2, \ldots, b_t^\lambda)$ is λ-best retrieved results from an external knowledge base (KB).
- **Goal**:

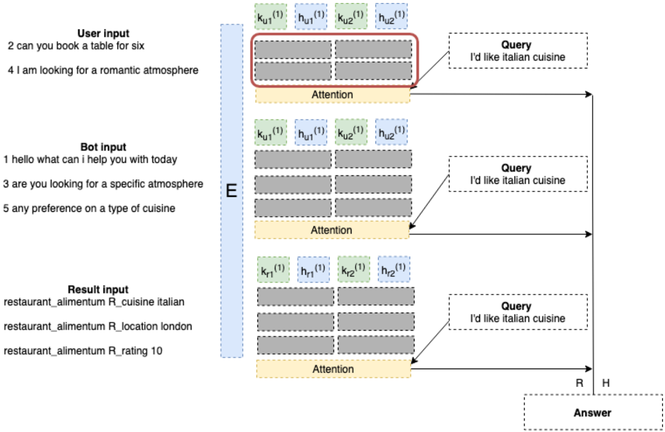
$$\psi_\Theta(\mathbb{U}_t, \mathbb{S}_{t-1}, \mathbb{B}_t) \rightarrow s_t. \qquad (2)$$

- **Solution**. Source-specific memories for different usage of words and syntactic structure.

2.1 Source-aware Recurrent Entity Network (SEntNet)



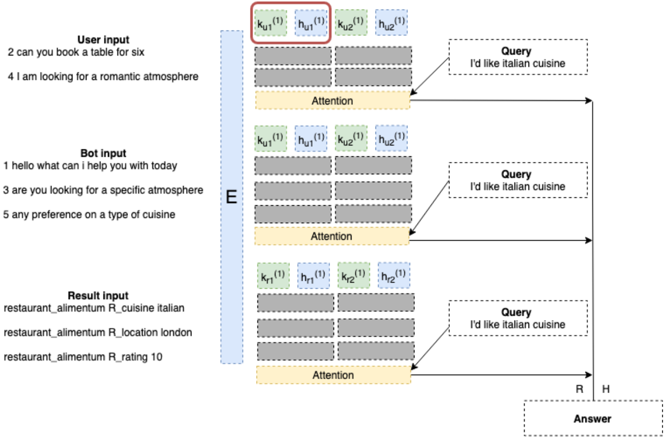
2.2 SEntNet – Input module



- The embedding of the i-th utterance $e_{i(\mathcal{S})}$ for source $\mathcal{S}$ is:

$$e_{i(\mathcal{S})} = \Sigma_x f_x \odot w_x^i + l_x^i \in \mathbb{R}^d. \tag{3}$$

2.2 SEntNet – Dynamic memory module (1)

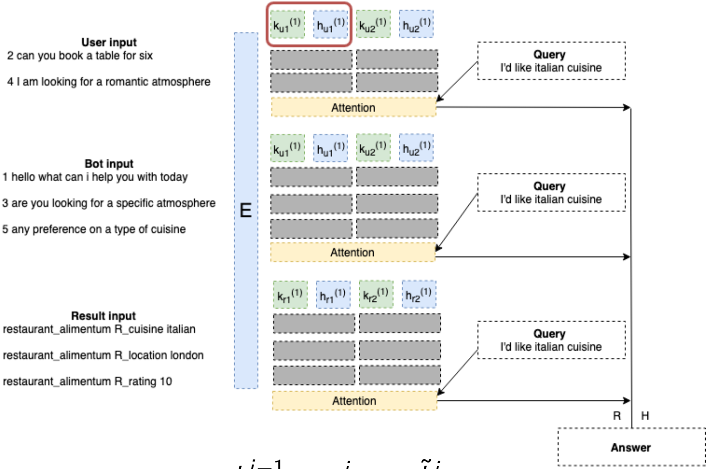


- For the i-th utterance from $\mathcal{S}$ in the dialogue, the memory block for the j-th entity is updated as:

$$g^i_{j(\mathcal{S})} = \sigma(e^T_{i(\mathcal{S})} h^{i-1}_{j(\mathcal{S})} + e^T_{i(\mathcal{S})} k^{i-1}_{j(\mathcal{S})}) \in \mathbb{R}^d \quad (4)$$

$$\tilde{h}^i_{j(\mathcal{S})} = \phi(G_{\mathcal{S}} h^{i-1}_{j(\mathcal{S})} + V_{\mathcal{S}} k^{i-1}_{j(\mathcal{S})} + W_{\mathcal{S}} e_{i(\mathcal{S})}) \in \mathbb{R}^d \quad (5)$$

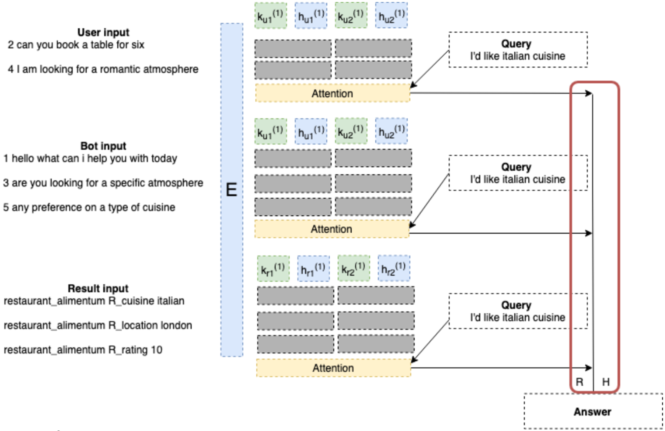
2.2 SEntNet – Dynamic memory module (2)



$$h^i_{j(\mathcal{S})} = \frac{h^{i-1}_{j(\mathcal{S})} + g^i_{j(\mathcal{S})} \odot \tilde{h}^i_{j(\mathcal{S})}}{\|h^{i-1}_{j(\mathcal{S})} + g^i_{j(\mathcal{S})} \odot \tilde{h}^i_{j(\mathcal{S})}\|} \in \mathbb{R}^d \tag{6}$$

$$h_{j(\mathcal{S})} = h^1_{j(\mathcal{S})} \oplus h^2_{j(\mathcal{S})} \oplus \cdots \oplus h^n_{j(\mathcal{S})}. \tag{7}$$

2.3 SEntNet – Output module (1)

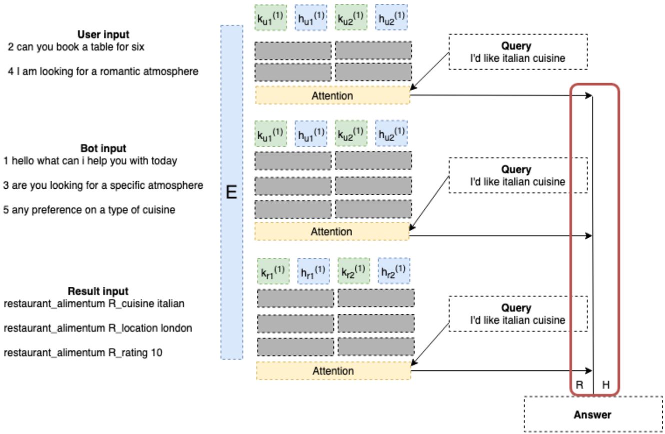


- Let $q \in \mathbb{R}^d$ be the embedding of the user utterance u_t for the current turn t. The output module is defined as:

$$p_{j(\mathcal{S})} = \mathrm{softmax}(q^T h_{j(\mathcal{S})}) \tag{8}$$

$$z_{\mathcal{S}} = \Sigma_j h_{j(\mathcal{S})} p_{j(\mathcal{S})} \in \mathbb{R}^d \tag{9}$$

2.3 SEntNet – Output module (2)



$$z = z_{\mathcal{S}_{\mathbb{U}}} \oplus z_{\mathcal{S}_{\mathbb{S}}} \oplus z_{\mathcal{S}_{\mathbb{B}}} \in \mathbb{R}^{3d} \tag{10}$$

$$y = L\phi(q + Hz) \in \mathbb{R}^{r} \tag{11}$$

$$y = \mathrm{softmax}(\tilde{y}_j). \tag{12}$$

3.1 Experimental setup: Datasets & Evaluation

- **Datasets**.
  - Dialog bAbI (Bordes&Weston,2017)
  - DSTC2 (Henderson et al.,2014).

Table: Statistics of the two datasets

	# dialogues	# words	# responses	Partitioning
bAbI	3,000	3,747	4,212	1000/1000/1000
DSTC2	2,785	1,229	2,406	1,168/500/1,117

- **Evaluation**. Turn-level accuracy – the fraction of correct responses out of all.

3.2 Experimental setup: Baselines

- **TF-IDF**. This model ranks candidate responses by TF-IDF weighted cosine similarity between one-hot vectors of input and candidate responses.
- **Query-to-answer (Q2A)**. Given a query, it finds the most common response in the train set (Weston et al., 2015).
- **DQMemNN**. This is the state-of-the-art for response selection on dialog bAbI dataset (Wu et al., 2018); for a fair comparison, we used DQMemNN without exact matching and delexicalization.
- **HHCN**. This is the state-of-the-art for response selection on the DSTC2 dataset (Liang and Yang, 2018).
- **EntNet**. We reproduced EntNet, which was originally introduced for question answering and is reported to have strong reasoning abilities (Henaff et al., 2017).

4 Results

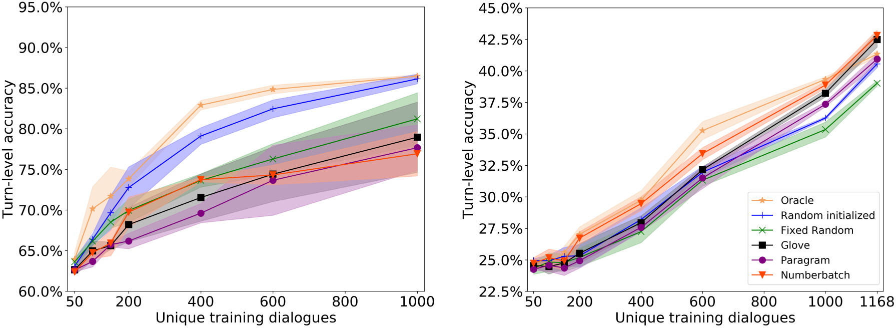
RQ1: How well does SEntNet predict appropriate responses?

Model	bAbI	DSTC2
TF-IDF	0.040	0.030
Q2A	0.570	0.220
EntNet	0.850	0.388
DQMemNN	0.863	–
HHCN	–	**0.661**
SEntNet	**0.910**	0.412

Table: Comparison with baselines on the bAbI and DSTC2 datasets.

4 Results

RQ2: How do different embeddings affect SEntNet's performance?



(a) bAbI

(b) DSTC2

Figure: Turn-level accuracy of SEntNet for different embedding spaces on bAbI and DSTC2 datasets. (Please note that the scales on the x-axes and y-axes differ.)

4 Results

RQ3: How well does SEntNet perform in the case of limited data?

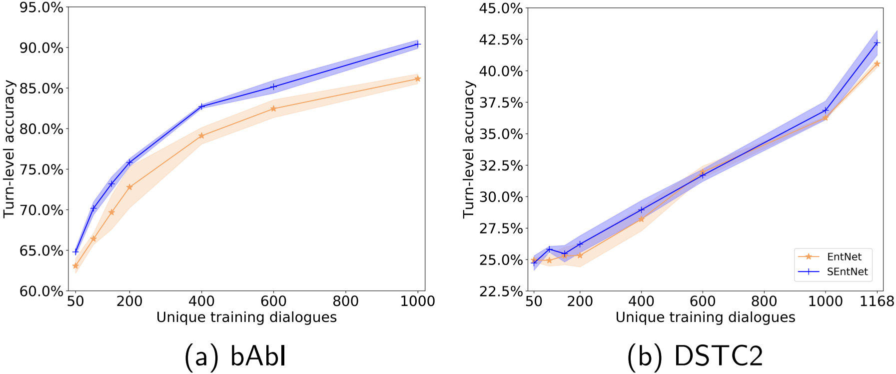


Figure: Turn-level accuracy of SEntNet on both datasets, when trained with different volumes of training dialogues. (Please note that the scales on the x-axes and y-axes differ.)

5 Conclusion & Future work

We propose **SEntNet**, a dialogue response selection model in memory network architecture:

- Select responses aware of source-specific history and consistently outperforms the baselines for end-to-end TDSs.
- Optimizing embeddings while training is useful for the performance.
- Tolerant of sparse data and able to handle different degrees of lexical diversity.
- Increase of learnable parameters by introducing extra memory modules can be addressed with parallel update mechanism design inherited from EntNet.

In the future work, we plan to apply the source-aware context idea that underlies SEntNet to other variant memory networks.

Thanks for your attention!
Q&A

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